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Spatial Analysis of the Vegetation Condition Index of Al-Hamdania District by Remote Sensing Dataset

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Abstract

Drought is a natural hazard that occurs as a result of decreased rainfall and water storage. It has a significant impact on the agriculture sector. In this paper, monitoring the drought in the Al-Hamdaiya district located east of Mosul city in the Nineveh Governorate, Northern Iraq, was performed for years 2017, 2018, 2019, 2022, and 2024 by integrating remotely sensed data and geographic information systems (GIS). Spatial and temporal distribution changes of the drought phenomenon for the study area were verified by Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI) using Landsat 8 (Operational Land Imager: OLI) images during April month. The results indicated that the study area experienced relatively no drought between 2019 and 2024. However, there was a significant increase in drought conditions during 2017, 2018, and 2022. The percentage of drought-free areas fluctuated between 11.73-91.58% from 2017-2024. Among the drought categories, extreme and moderate drought accounted for the largest percentages, followed by severe and mild drought.

Keywords: VCI, GIS, Remote Sensing, Hamdania, NDVI

التحليل المكاني لمؤشر حالة الغطاء النباتي لقضاء الحمدانية باستخدام معطيات التحسس النائي

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الخلاصه

الجفاف هو احد المخاطر الطبيعية التي تحدث نتيجة لانخفاض هطول الأمطار وتخزين المياه، وله تأثير كبير على القطاع الزراعي. في هذا البحث, مراقبة حالة الجفاف في قضاء الحمدانية تقع شرق مدينة الموصل في محافظة نينوى، شمال العراق للأعوام (2017،
2018، 2019، 2022، و2024) انجزت باستخدام التكامل بين بيانات الاستشعار عن بعد ونظم المعلومات الجغرافية (GIS) . تم التحقق من التغيرات المكانية والزمانية في توزيع ظاهرة الجفاف في منطقة الدراسة من خلال مؤشر الغطاء النباتي الطبيعي (NDVI) ومؤشر حالة الغطاء النباتي (VCI). باستخدام المرئيات الفضائية للقمر الاصطناعي (Landsat 8 (Operational Land Imager: OLI) خلال شهر نيسان للسنوات المعتمدة في الدراسة. اظهرت نتائج إلى أن منطقة الدراسة لم تشهد جفافًا بين عامي 2019 و2024. ومع ذلك،

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كان هناك زيادة كبيرة في حالة الجفاف خلال أعوام 2017 و2018 و2022. وتراوحت نسبة المناطق الخالية من الجفاف بين 11.73% و91.58% خلال الفترة من 2017 إلى 2024. وشملت الفئات التالية : الجفاف الشديد والمتوسط يشغل اكبر نسبة مئوية ، يليه الجفاف الشديد والخفيف

1. Introduction

Rapid urbanization has significant environmental consequences, including natural resource depletion, regional and global climate change, and reduced human well-being. One considerable effect of urban expansion is the permanently converting large areas of natural vegetation and agricultural land into impermeable surfaces, resulting in major changes to land surface characteristics [1]. Among the other effects of climate change, drought is a significant phenomenon, marked by a decrease in overall precipitation that leads to water shortages in different regions [2,3]. Drought significantly affects the quantity and quality of vegetation, often resulting in reduced plant cover [4, 5]. In the last century, research on drought indicators has improved the monitoring and assessment of drought severity, duration, and spatial-temporal distribution patterns [6-8]. Vegetation indices (VIs), generated from surface reflectance in multiple bands, are valuable for (potentially) salient vegetation properties being highlighted [9]. These indices are derived from reflectance characteristics of plants (e.g., the absorption and reflection of different spectral bands). An example of an important vegetation index is the Vegetation Condition Index (VCI) that relates the current NDVI to the values of NDVI for the same time of the year in previous years. The Vegetation Condition Index (VCI), presented as a percentage, is the relative to the local observed NDVI value of the historical observed NDVI values. Lower values indicate worse vegetation conditions, and higher values represent better vegetation health [10]. The NDVI is based on the fact that the mesophyll layer of plants reflects near-infrared (NIR) radiation and absorbs radiation of the red spectral band [11,12]. The effect of climate change on NDVI is more sensitive in dry and semi-arid areas[13].

To track vegetation health, as well as monitor vegetation productivity, different spectral bands are used by different remote sensing methods. Remote monitoring of vegetation is essential for the long-term tracking of ecosystems, forestry management, fire ecology, drought evaluation, and agricultural production forecasting [13,14]. Several indices such as NDVI and VCI are popularly used to monitor vegetation states through remote sensing technologies as it was conducted in the present study. The NDVI is commonly applied to estimating green vegetation, and the VCI is beneficial to monitoring agricultural drought in particular. VCI integrated with GIS and remote sensing technology increase the reliability and efficiency of the surveillance of the agricultural drought condition [15]. The application prospectiveness of spatial analysis of the VCI has been demonstrated in recent studies. Wang et al. (2021) [16] employed VCI to study the effect of a drought on vegetation in Mongolia and reported strong spatial heterogeneity in plant response to the drought[17]. Liu et al. (2022) [18] A spatial phantom correlation test was used to map the areas in the Loess Plateau region of China where vegetation degradation was still a problem, but where the soil erosion effects along with land use changes would have an impact on the vegetation dynamics. The capability of the VCI in agriculture has been used to forecast deviation in yield and to measure crop condition as early warning options for food security were developed[19]. The results of this study highlight that spatial analysis is a necessary element for the understanding of complex links between vegetation and its environment. Although widely used, there are certain levels of difficulty in applying of VCI and spatial analysis. Multisource data integration and interdisciplinary approaches are essential for spatial analysis of the VCI.Combining these remote-sensing derived data with socioeconomic databases, climate models and ground-based observations could provide greater insight into vegetation dynamics and their drivers [18,20]. Rahimabadi and Azarnivand (2022)[21] analysed the impact of human activities and climate on the vegetation based on VCI data and land use maps. The spatial analysis of the VCI can provide valuable information to make strategies in resource management and policy beyond academic research. Inability to apply all methods to all areas and institutions means conservation efforts and land reclamation plans would benefit if it were possible to locate areas with declining vegetation. In agriculture, VCI-based monitoring can also be useful for the precision farming process, to enable the farming community to obtain information on the maximization of fertilization and irrigation strategies, such as from [19].The ongoing research is intended to investigate the spatio-temporal variation of vegetation cover and agricultural drought in the Al-Hamdania district during 2017, 2018, 2019, 2022, and 2024 seasons using NDVI and VCI spectral indices. There have been severe environmental problems in the district, such as severe and extended drought, desertification and changes in land use have a negative effect on the vegetation health. Hence, understanding the spatial distribution of the vegetation conditions in Al-Hamdania district would be important for planning proper land management and for compensating the impacts of environmental degradation. The VCI analysis is an excellent chance to evaluate the health of the district's vegetation and locate the places where focused intervention is needed using remote sensing. The study's findings would increase the knowledge of climate variability on agricultural productivity and ecosystem sustainability.

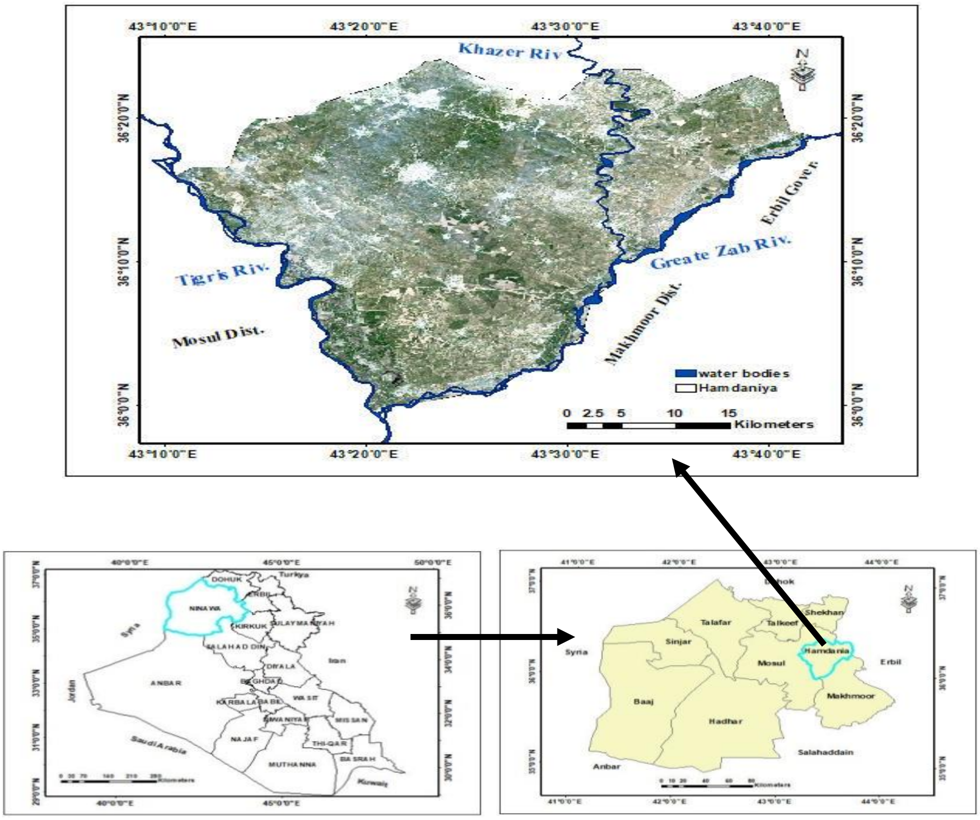


Figure 1: Study area location

2. Materials and Methods

2.1 Study Area

The study was performed in the Al-Hamdaiya district, east of Mosul city, which is in Northern Iraq, Nineveh Governorate. The district is located in ¬ latitudes 36º00'00" -36º21'14" N and longitudes 43º13'53"-43º42'12.2"E, Figure 1. It has a total area of 1158.86 km2 with topography lying between 123 and 539 m above mean sea level, Figure 2. Its country is inquiring from flat to gently rolling with undulations in the southwest, which contain many valleys and inclines indicative of a general trend downward.The study area belongs to the semi-arid agro-climatic zone, which falls under the Köppen Geiger climate type and also lies in the semi-arid climate (BSk) zone. Its features are the following: the rain falls swiftly in winter and early spring, the summer is hot and dry with temperatures over 40°C.Low VCI values would generally imply low crop production. Such a relationship underscores the role of VCI as an agricultural drought monitoring tool. The results should contribute to early warning and decision making on crop management, irrigation planning, and food security analyses.

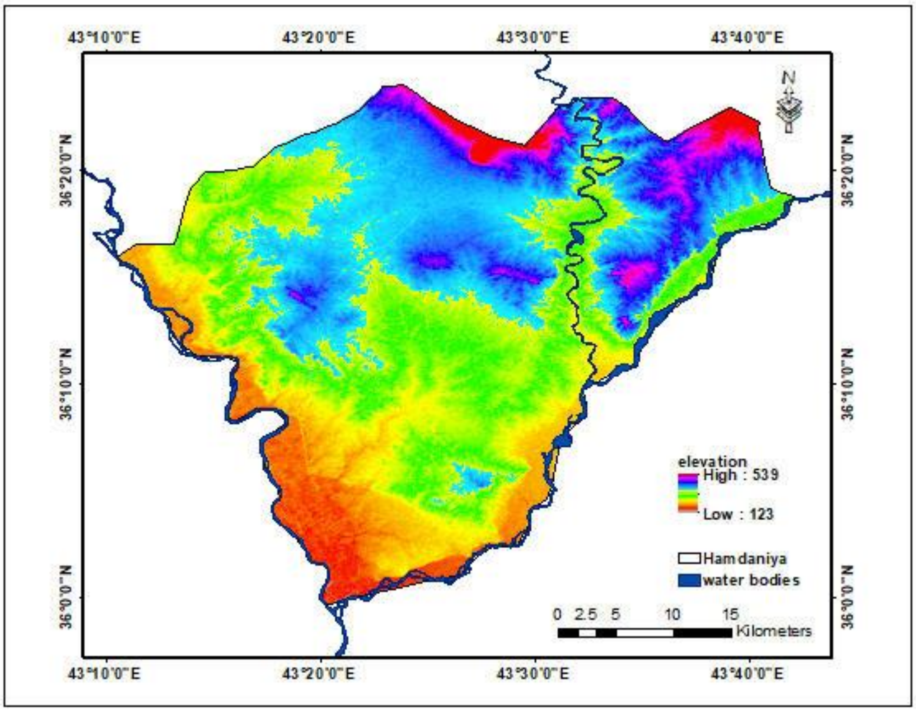


Figure 2: Topographic elevation of the study area

3. Dataset

Landsat images generated specific drought indices to monitor the agricultural drought. Landsat 8 images (path: 170/ row: 35) of collection 2 level-2, dated 2017, 2018, 2019, 2022, and 2024, which covered the study area, were used, Figure 3. These images were certified as Landsat Collection 2 Level-2, with radiometric, thermal, and geometric correction in the projection of the universal Transverse Mercator (UTM) and zone 38N and datum of the World Geodetic System: WGS84) (https://www.usgs.gov/media/files/landsat-8-9-collection-2-level-2-science-product-guide). Table 1 illustrates the satellite imagery utilized in this investigation and the dates and details of their acquisition, which are found at (https://www.usgs.gov/landsat-missions/landsat-8). The aforementioned imagery was obtained without charge from the United States Geological Survey (USGS) website, which may be found at http://earthexplorer.usgs.gov. The study adopted April as the main growth period for wheat and barley crops in the Al-Hamdaniya district based on the region's prevailing climatic and environmental conditions.

Table 1: Specifications of the used Landsat 8 satellite images (collection 2 level 2)

Satellite	Sensor ID	Spectral bands	Spatial Resolution (m)	Wavelength (µm)	Path and Raw	Date of Image
Landsat 8	OLI	Band-2 Band-3 Band-4 Band-5	30	Visible/ Blue 0.450-0.51 Visible / Green 0.53-0.59 Visible / Red 0.630-0.67 Near IR 0.85-0.88	P-170 R-35	29/4/2017 17/04/2018 6/04/2019 4/04/2022 25/04/2024

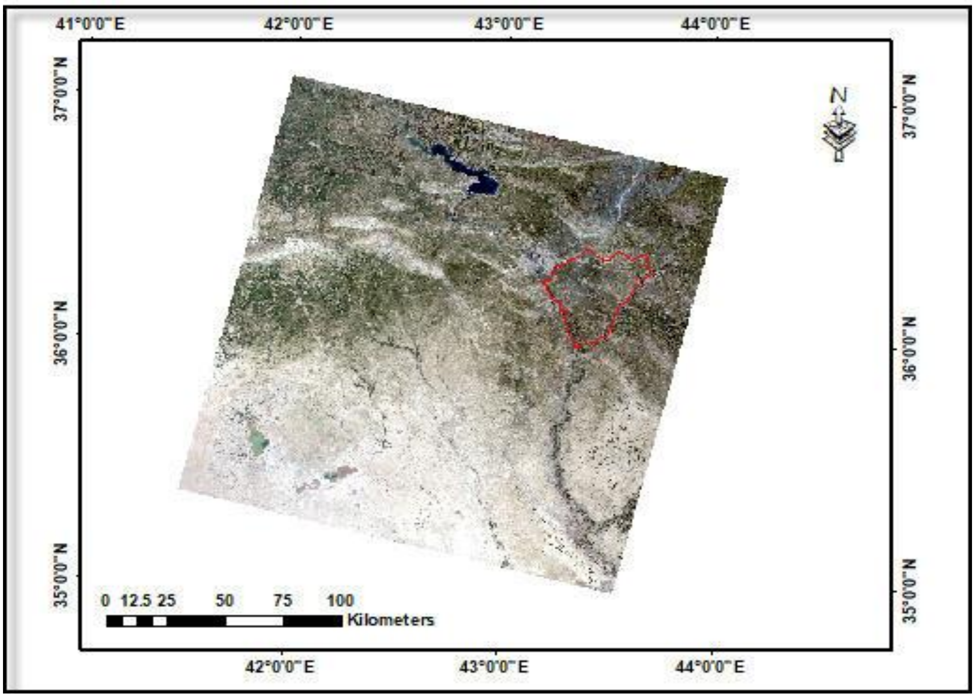


Figure 3: Landsat 8 image (natural color 4,3,2) of the study area (Path=170, Raw=35)

4. Determination of VCI

To determine VCL, the NDVL was calculated, one of the most commonly used vegetation indices for assessing biomass production capability, land cover, and plant growth. In Landsat 8, it was computed using the following Equation [23]:

$$NDVI = \frac{NIRband - Redband}{NIRband + Redband} \quad (1)$$

Where: NIR is the band of near-infrared reflectance, and Red is the band of red reflectance.

The NDVI values vary from ($^{-}1$ to $^{+}1$). A higher NDVI value indicates the existence of healthy vegetation in the region, whereas lower values indicate sparse vegetation. In detail, water bodies typically exhibit a Normalized Difference Vegetation Index (NDVI) value of less than zero. Bare soils generally range between 0 and 0.1, while vegetative surfaces have NDVI values exceeding 0.1 [24]. In this work, the NDVI values were calculated using Landsat8 satellite images of the April months for each year 2017, 2018, 2019, 2022, and 2024 using ArcGIS/spatial analyst /raster calculator tool. April was adopted as the main growth period for wheat and barley crops in Al-Hamdania district in Nineveh Governorate based on the region's prevailing climatic and environmental conditions. The VCI, which is based on the relative NDVI alteration concerning the minimum and maximum historical NDVI values [25], was utilized to determine the drought conditions using the following Equation [10]:

$$VCI = \frac{NDVIi - NDVImin}{NDVImax - NDVImin} \tag{2}$$

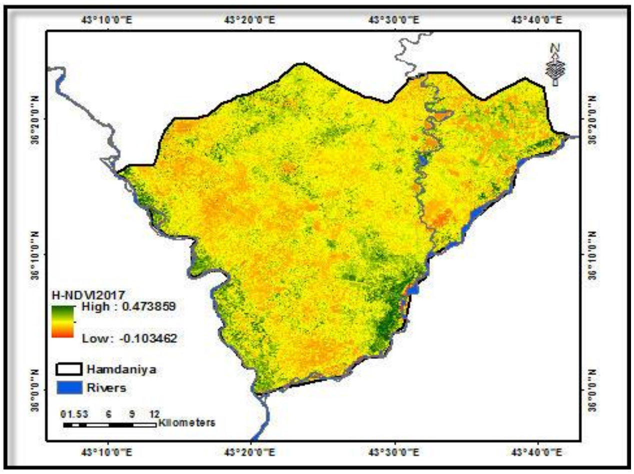
NDVIi stands for the current year's NDVI and NDVImax, and NDVImin stands for the adopted years' maximum and minimum NDVI values, respectively. NDVImin and NDVImax were computed using ArcGIS's pixel statistic tool. The maximal and minimal vegetation phenology dynamics are represented by the percentages 0–100 that make up the VCI value. The classes of VCI values are listed in Table 1. The NDVI and VCI values support the study objective by monitoring spatial and temporal drought, identifying vegetation health and stress, and assessing drought severity with VCI in the Al-Hamdania district.

Table 2: Classes of VCI drought index [26]

VCI	Values
Extreme drought	< 10
Severe drought	< 20
Moderate drought	< 30
Mild drought	< 40
No drought	≥ 40

5. Results and Discussion

Drought characteristics are important factors to be identified for analyzing drought monitoring. The statistics taken from the five drought maps using the NDVI-based VCI index, described by Eq.1 and 2, form the basis of the change detection analysis reported in this paper. Figures 4-8 depict the spatial and temporal variations of the NDVI in the study area for the adopted years. The NDVI for 2017, 2018, and 2022 can be classified as moderate vegetation cover. The high dense vegetation cover types were observed in 2019 and 2024. Figures 9 and 10 show the NDVImin and NDVImax maps of all the years adopted in the study. These raster maps were important for solving Eq. (2) to find the VCI.



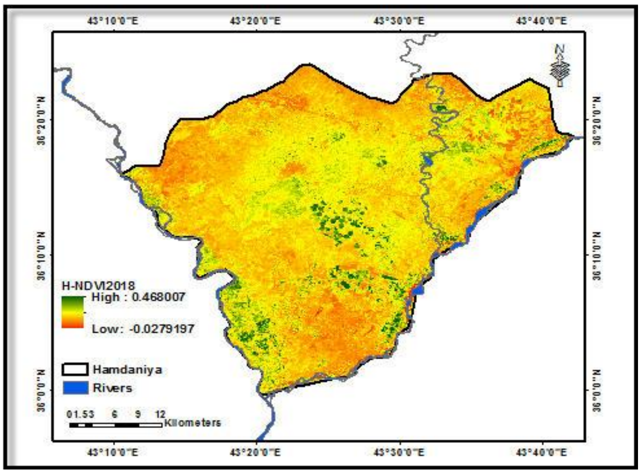
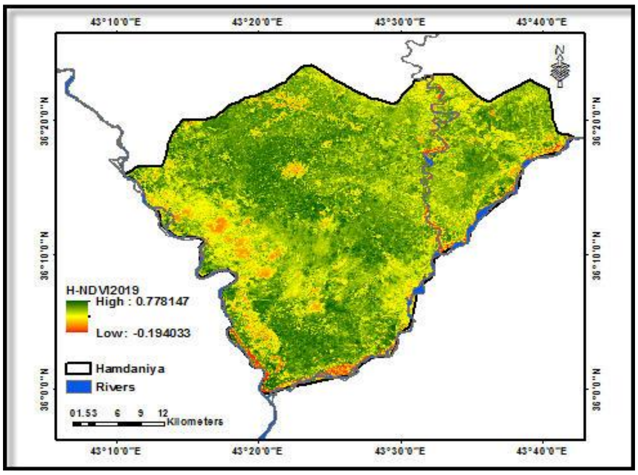


Figure 4: NDVI map of the study area, 2017 **Figure 5:** NDVI map of the study area,2018



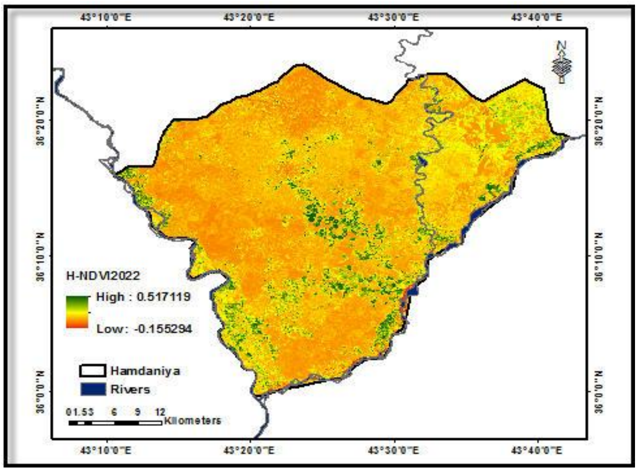


Figure 6: NDVI map of the study area,2019 **Figure 7**: NDVI map of the study area,2022

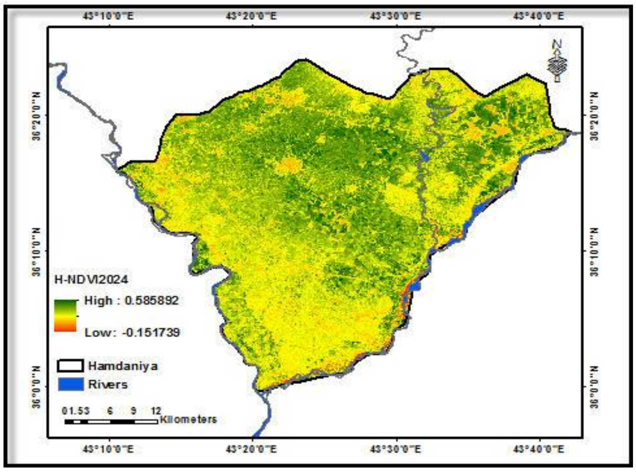


Figure 8: NDVI map of the study area,

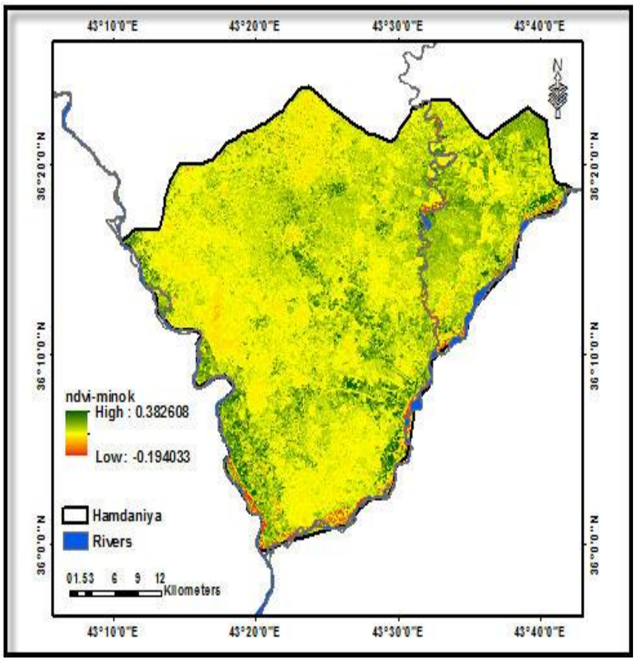


Figure 9: The Minimum statistical NDVI

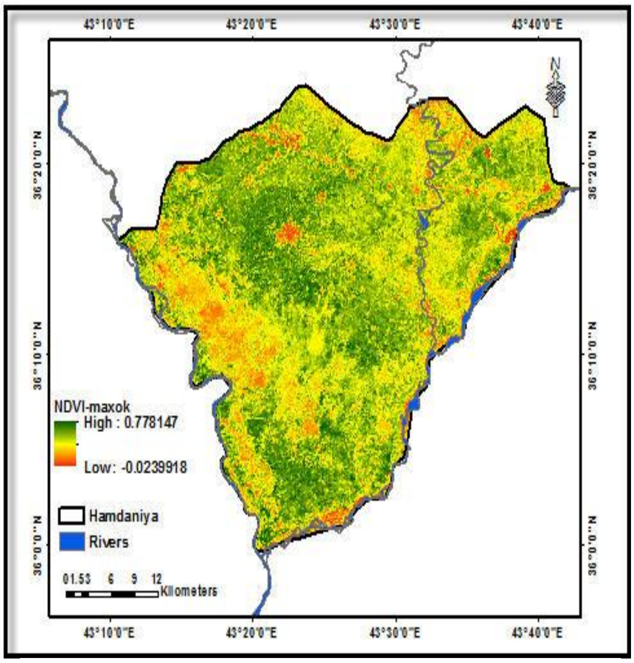


Figure 10: The Maximum statistical NDVI

Figures 11-15 show the drought classes' spatial and temporal distribution based on the VCI index. The figures show that 2019 recorded the largest percentage of the non-drought area, 1061.317 km^2 (91.583%), due to the high rainfall quantity for this year; it has reached 497mm in the study area, according to the Iraqi Agricultural Meteorology Center [20], then 2024 779.788 km^2 (67.289%). The high drought-affected area was shown in the year 2022 at 926.937 km^2 (79.994%) in the forefront due to the very low quantity of rainfall in this year (163mm), then 2017 at 235.198 km^2 (20.296%) and 2018 at 172.503 km^2 (14.885%). The figures indicate that 2022 experienced the most extensive drought-affected area (79.994%), coinciding with the lowest recorded rainfall of 163mm. This suggests that regions within Al-Hamdania that receive less precipitation or have lower water retention capacities may be more vulnerable to extreme drought. Several factors that could contribute to more prone to extreme drought within the study area include topography and elevation, soil composition and water retention, and human activities, such as excessive groundwater extraction, inadequate irrigation, and deforestation.

More details of the VCI drought class area and its percentage are listed in Tables 3 and 4, respectively. The area for extremely, severe, moderately, mild, and no drought classes for each adopted year was illustrated in Figure 16. Drought is essentially based on rainfall patterns or, more specifically, the lack of sufficient rainfall over a long period. By identifying rainfall-drought relationships and their implications for water resource management and climate change adaptation, the findings from the study of spatial and temporal changes in the study area (which is located within semi-arid regions) are crucial for understanding the region's drought trend and the factors influencing its expansion and spread. They may help develop mitigation strategies, increase resilience, and ensure sustainable development in semi-arid regions.

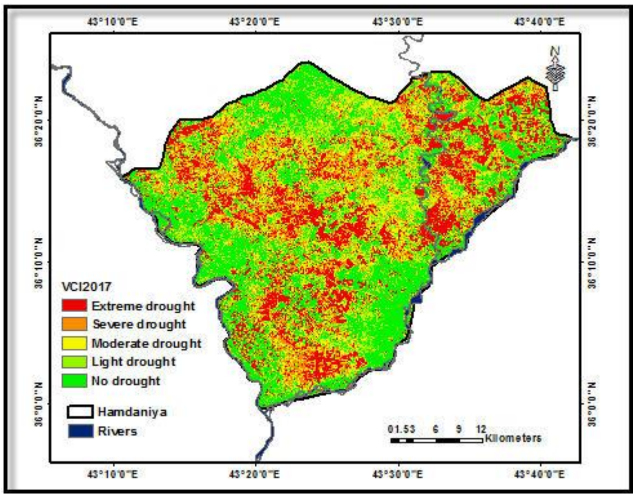


Figure 11: Spatial Distribution of VCI , 2017

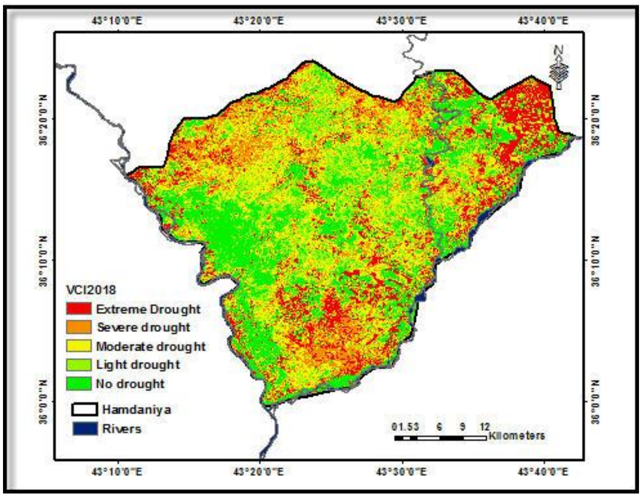


Figure 12: Spatial Distribution of VCI , 2018

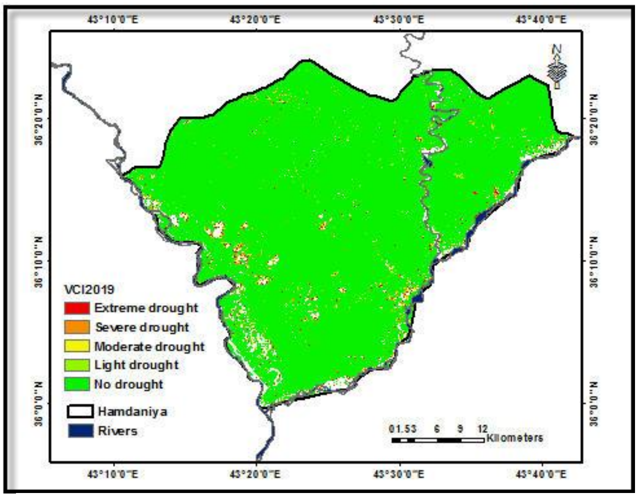


Figure 13: Spatial Distribution of VCI , 2019

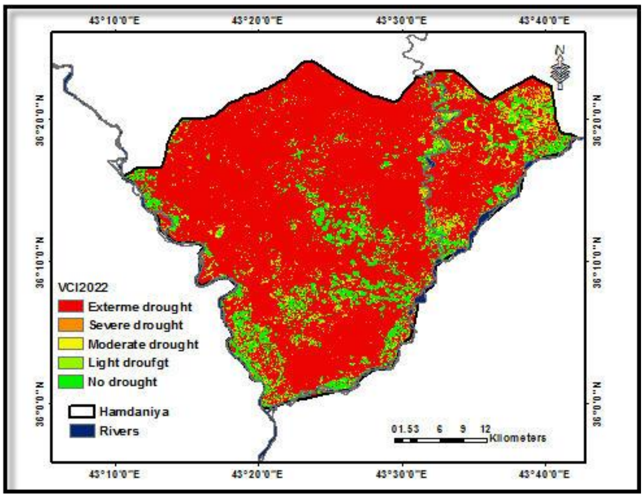


Figure 14: Spatial Distribution of VCI , 2022

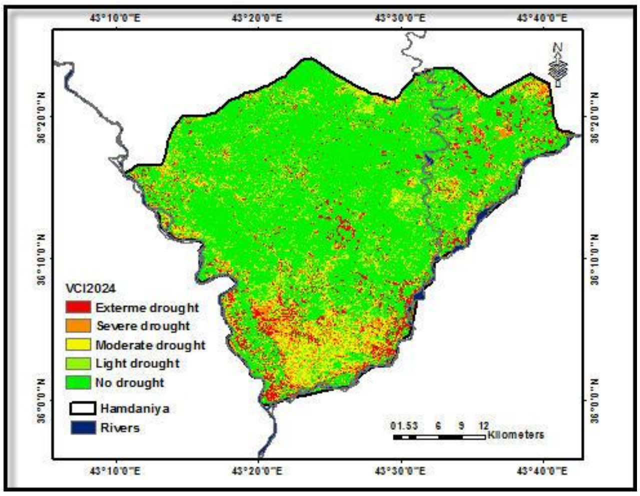


Figure 15: Spatial Distribution of VCI , 2024

Table 3: Area of VCI drought classes of the adopted years

VCI	Y-2017	Y-2018	Y-2019	Y-2022	Y-2024
Extreme	235.198	172.503	65.969	926.937	79.522
Severe	172.972	200.376	9.368	38.607	72.965
Moderate	188.597	280.244	10.203	30.738	108.452
Mild	177.502	209.282	12.000	26.541	118.130
No	374.589	296.453	1061.317	135.929	779.788

Table 3: Percentage of area VCI drought classes of the adopted years

VCI	Y-2017	Y-2018	Y-2019	Y-2022	Y-2024
Extreme	20.296%	14.885%	5.693%	79.994%	6.862%
Severe	14.926%	17.290%	0.808%	3.332%	6.296%
Moderate	17.137%	24.183%	0.880%	2.653%	9.358%
Mild	15.317%	18.059%	1.036%	2.291%	10.193%
No	32.324%	25.581%	91.583%	11.731%	67.289%

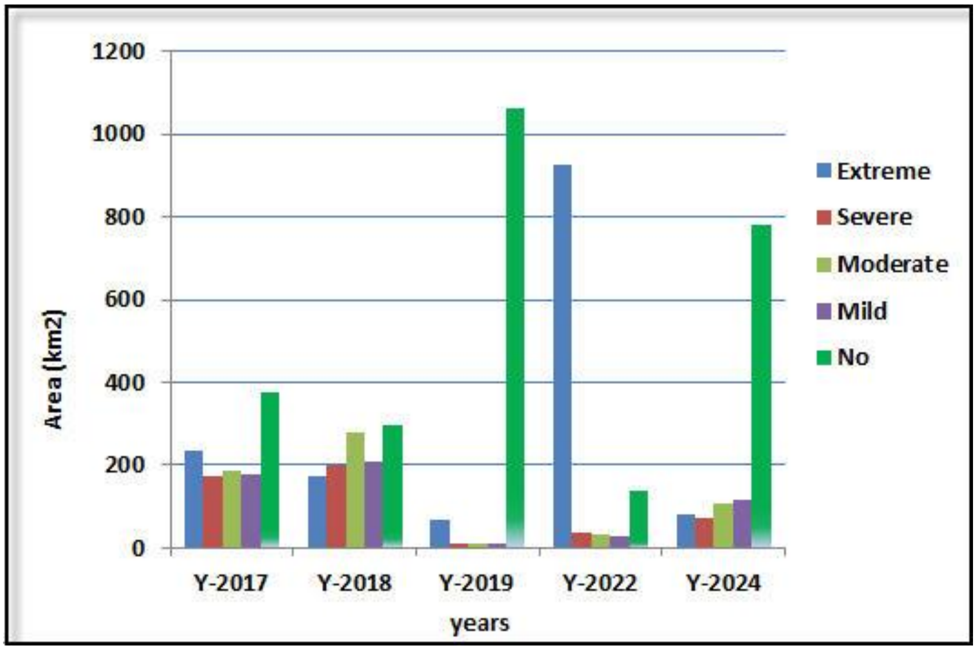


Figure 16:: Area of VCI drought classes related to the adopted years

Based on the foregoing, the study of multi-drought maps using the NDVI-based Vegetation Condition Index (VCI) is projected to produce many major discoveries, which can be presented as follows:

1. Drought conditions vary spatially.

The VCI maps likely show significant spatial variability in drought conditions throughout the research area. Regions with lower VCI values (showing poor vegetation) are designated drought-affected, while those with higher VCI values are classified as normal or favorable. This spatial diversity can be attributed to local climate variables, soil types, land use patterns, and water availability. The findings can assist in identifying drought sensitivity regions, which are crucial for developing focused mitigation and adaptation efforts.

2. Temporal Patterns in Drought Severity
Time sequential maps of VCI may reveal patterns in drought intensity during the research period. For example, certain years or seasons may have persistently low VCI levels, indicating long-term or severe drought conditions. These temporal trends can be connected with past climatic data (for example, rainfall patterns and temperature anomalies) to understand the causes of droughts better. The findings can show whether drought frequency or intensity rises over time, which is critical when analyzing climate change implications.

3. Correlation between VCI and Agricultural Productivity
VCI levels are projected to negatively connect with agricultural production metrics, including crop yield and vegetation cover. Low VCI readings are likely to indicate reduced agricultural yields. This correlation emphasizes the importance of VCI as a tool for monitoring agricultural drought. The findings can help inform early warning systems and decision-making for crop management, irrigation planning, and food security assessments.

6. Conclusions

Information that can derive from multi-drought maps generated using the NDVI-based VCI index would contribute substantially to understand the geographical and temporal patterns of drought, its effect on vegetation and agriculture and its interactions with other environmental and climatic variables. Such results provide a valuable tool to enhance our understanding of how drought evolves and guide the development of evidence-based decision support for drought risk management and mitigation.

The results obtained lead to a lot of important conclusions, including:
1. The region of the drought area expanded..
2. The drought-free occurred by 32.324%, 25.581%, 91.583%, 11.731% and 67.289% in 2017, 2018, 2019, 2022 and 2024 among the five drought-free-year rates.
3. Severe and extreme drought classes had the highest percentage in the study area which was then followed by moderate and mild drought.
4. Between 2017 and 2022, the region was stricken by severe agricultural droughts. This is because there hasn't been enough rain. This drought is more severe due to the dependence of farmers on rain-fed agriculture, especially on wheat and barley farming, resulting in low agricultural productivity.
5. The findings in this paragraph are that droughts in the study area have had severe effects on agriculture and water resources, mainly because the area relies heavily on rainfed agriculture. Due to diminishing rainfall, the production of staple crops such as wheat and barley declined to such an extent that not enough had been produced to meet the needs farmers.
In conclusion, dealing with these issues in Al-Hamdania district requires an integrated approach that looks at combating the impacts of drought at different levels, such as improving the management of the water resources, applying modern agricultural practices such as conservation agriculture, and supporting the farmers to help them mitigate and adapt to the climate change.

7. Acknowledgements

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