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Land Use Change and Its Implications for Drought Dynamics in Sulaymaniyah Governorate between 2013-2022.

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ABSTRACT

Drought is a significant phenomenon associated with climate change, impacting various sectors. Effective planning is essential to mitigate its effects and minimize potential damage. Remote sensing data and GIS-based spatial analysis were employed to assess drought conditions. This study focuses on Sulaymaniyah Province, located in northeastern Iraq, covering an area of 21,240 km². Geographically, the province lies between longitudes 44°49'59" E and 45°59'43" E, and latitudes 34°21'07" N and 36°15'48" N. The study utilized Landsat 8 OLI satellite data to derive two key spectral indices: The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). These indices were analyzed using ArcGIS 10.4.1 to assess drought conditions and their spatial distribution across the region. Maps highlighting NDVI and NDWI values were created to evaluate the drought impacts for the years 2013, 2017, 2021, and 2022.The findings indicate a clear spatial variation in drought severity across the province. NDVI analysis from 2013 to 2022 shows notable vegetation cover fluctuations, with low vegetation increasing from 43.7% to 66.5% in 2021 and dense vegetation peaking at 11.9% in 2017 before declining sharply. NDWI analysis indicates a rise in extremely drought-affected areas from 17.4% to 34.8%, while no-drought zones decreased from 0.6% to 0.1%. These findings reflect increasing water stress and environmental changes in Sulaymaniyah Governorate. Vegetation density declined after 2017, and drought severity worsened. NDI increased from 0.42 in 2013 to 0.53 in 2022, indicating a growing disparity between plant health and water availability, suggesting worsening drought conditions in Sulaymaniyah Governorate.

Keywords: *Drought, Sulaymaniyah, NDVI, NDWI, GIS.*

INTRODUCTION

Drought is a significant environmental issue affecting agriculture, water resources, ecosystems, and human communities. Identifying drought-related research gaps is crucial to advancing our understanding and developing effective mitigation and adaptation strategies. Drought is a difficult-to-predict but potentially life-threatening natural disaster. Meteorological drought variables rely on precipitation and temperature, applied locally or regionally based on data availability and the distribution of ground stations [1]. Drought, resulting from low rainfall periods, can affect any part of the Earth, including humid regions [2]. Its impacts extend to ecological and economic systems and may lead to population displacement. In addition, frequent droughts induce desertification [3]. Iraq has experienced severe drought over recent decades, marked by a significant decline in rainfall and a noticeable reduction in the flow of its major rivers [4]. The effects of drought can occasionally pollute water supplies [5]. The need for agricultural goods has surged due to the growing population's rising demand for food. The continued impact of reduced rainfall and the harmful consequences of drought are still presenting challenges and also lead to considering Iraq as an extremely prone zone of drought [5] and [6]. One of the common methods for drought monitoring is the use of satellite-based indices, which have been proven to be an effective method and an easy tool in previous studies [7]. NDVI is a proxy index for assessing vegetation cover and health, indicating plant health indirectly [8]. Monitoring drought involves assessing vegetation cover and health, which is crucial for gauging temperature and moisture stress. Changes in NDVI time series reflect alterations in climatic parameters like temperature or precipitation [9]. The Normalized Difference Water Index (NDWI) is a method of analyzing data to assess water resources [6]. NDWI is a remote sensing-based indicator sensitive to changes in leaf water content [10]. NDWI had a faster response to drought conditions than NDVI [11]. Remote sensing data can provide real-time surface information, while geographic information systems (GIS) can be used to analyze potential craters. Remote sensing has advanced land surface mapping, enabling improved drought-related monitoring on both temporal and spatial scales compared to conventional methods. GIS facilitates spatial analysis, such as identifying potential troughs in an area [12, 13]. Several studies have reported that using remote sensing and geographic information systems is an essential technique through spatial and temporal data obtained from reflectance, spectral indices, and spectral ratios to assess healthy vegetation, soil, land desertification, and drought [14]. Several drought indices have been developed and applied to the degree of duration and severity of drought and desertification, such as the Normalised Differential Vegetation Index (NDVI) in the Sulaimaniyah area, as in [15] and [16]. This study aims to analyze the changes in land use and land cover in Sulaymaniyah Governorate and their impact on drought dynamics over 10 years. The study also seeks to assess the relationship between vegetation health (NDVI) and water availability (NDWI) to understand their role in drought severity. Finally, the research aims to provide insights into the implications of land use changes for managing and mitigating drought conditions in the region.

Materials and Methods

2.1. Study Area

The study area is located in the northeastern region of Iraq, between longitudes 44°49'59" E - 45°59'43" E and latitudes 34°21'07" N - 36°15'48" N (Figure 1). Sulaymaniyah Province spans an area of 21,243 km^2. The climate of the Sulaymaniyah province is described as arid and semi-arid [17]. Satellite data (Landsat 8 OLI) was used as a series consisting of several USGS visualizations that were downloaded from a data Centre at http://earthexplorer.usgs.gov, With a spatial discrimination capacity of 30 m and a temporal resolution every 16 days. This study used images taken in April (2013, 2017, 2021, 2022) for the entire study area. Drought indicators were derived using this data, and these Indicators were monitored to estimate the evolution and severity of drought for the study area.

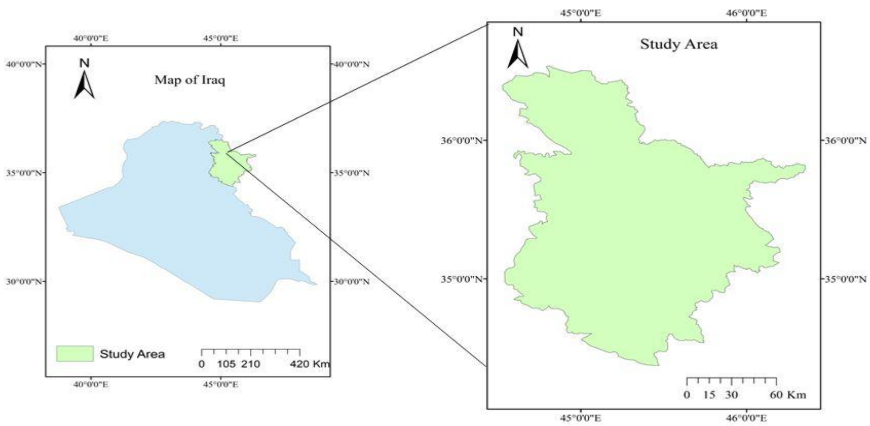

Figure 1: Study Area and Geographical map of Sulaymaniyah Province, Iraq.

2.2. Normalized Difference Vegetation Index (NDVI)

Multispectral satellite images enable rapid determination of vegetation density [18]. It is extracted by combining red and near-infrared (NIR) bands, indicating chlorophyll presence [19]. These bands are key due to their sensitivity to chlorophyll absorption, plant biomass, and their ability to differentiate between vegetation, land, open land, and water. NDVI results assign coefficient values; low values represent non-vegetated land (e.g., water, residential, or open areas), while high values signify dense vegetation [20]. NDVI effectively displays vegetation density, influenced by leaf cellular structure and chlorophyll pigmentation [6]. See Equation 1 for the NDVI algorithm.

$$NDVI = \frac{NIR(B5) - Red(B4)}{NIR(B5) + Red(B4)} \quad \ldots\ldots\ldots\ldots\ldots\ldots \textbf{(1)}$$

Equation 1 can be described as follows: NIR represents the near-infrared reflectance value, found in band 5, while red represents the red color reflectance value, found in band 4. The NDVI processing results yielded values ranging from -1 to +1. In this case, an increase in value indicates higher vegetation density. NDVI can provide information on temperature gradients of vegetation areas, land use types, and vegetation species identification [13, 19].

2.3. Normalized Difference Water Index (NDWI)

NDWI estimates soil and canopy moisture content using spectral values from satellite images [21] and [22]. It indicates surface wetness, with lower values denoting dryness and higher values indicating wetness. NDWI is commonly employed for drought detection based on vegetation moisture, as in this study, where it assessed humidity and dryness using satellite data. Utilizing near-infrared (NIR) and shortwave infrared (SWIR) bands, NDWI leverages NIR reflectance to discern dry leaf structure and SWIR reflectance to gauge changes in plant moisture content and mesophyll structure [23]. By combining NIR and SWIR bands, NDWI enhances accuracy by accommodating differences in internal leaf structure and dryness [24]. See Equation 1 for the NDWI algorithm.

$$NDWI = \frac{SWIR(B6) - NIR(B5)}{SWIR(B6) + NIR(B5)} \quad \ldots\ldots\ldots\ldots\ldots \textbf{(2)}$$

In Landsat 8, NIR reflectance is in band 5, and SWIR reflectance is in band 6. NDWI is affected by leaf moisture content, vegetation type, and land cover in calculating the wetness index [11]. High NDWI values signify abundant vegetation water content, whereas low NDWI values suggest sparse vegetation water content and low vegetation density.

2.4. Normalized Drought Index (NDI):

The Normalized Drought Index (NDI) is a metric used to assess drought conditions by comparing vegetation health (NDVI) and water availability (NDWI). It is calculated as the difference between average NDVI and NDWI, normalized by their sum. A higher NDI indicates better vegetation health relative to available water, while a lower NDI suggests increasing drought severity.

A simple drought coefficient (NDI) was calculated using a normalized difference of $NDVI_{avg}$ and $NDWI_{avg}$ as follows:

$$NDI = \frac{NDVIavg - NDWIavg}{NDVIavg + NDWIavg} \text{…………} \mathbf{(3)}$$

$$NDVI_{Avg} = \frac{Weighted\ Sum}{Total\ area} \text{…………..} \mathbf{(4)}$$

$$NDWI_{Avg} = \frac{Weighted\ Sum}{Total\ area} \text{…………} \mathbf{(5)}$$

Result and Discussion

3.1. Normalized Difference Vegetation Index (NDVI)

This study produces a range of values from -0.05 to 0.787 using the NDVI algorithm. Higher NDVI values indicate greater vegetation greenness (chlorophyll levels), while lower NDVI values indicate reduced vegetation greenness (chlorophyll levels). Therefore, the NDVI value can be used to visualize vegetation density and drought levels in an area. Lower NDVI values correspond to lower vegetation density and a higher probability of drought, whereas higher NDVI values indicate higher vegetation density and a lower probability of drought. The NDVI index was used as an important criterion to evaluate the state of drought by analyzing vegetation cover in terms of its density and area, as shown in Table 1 and Figure 2. The prevalence of the low vegetation type in all years and the highest area was recorded in 2021 at 66.5%, after it was 43.7% in 2013, then decreased to 39.97% in 2022. As for the medium vegetation type, its highest area was recorded in 2013 at 51.75%, then it decreased during subsequent years to 43.08%, 30.78%, and 39.97% for the years 2017, 2021, and 2022, respectively. Straight. As for the dense vegetation type, it constituted the smallest area for all years of the study, as the highest area was recorded in 2017, at a rate of 11.93%, and the lowest area was recorded in 2021, at a rate of 1.88%. The above results showed that the density and areas of vegetation cover fluctuated during the years of the study, affected by the amounts of rainfall and repeated droughts to which the study area was exposed.

Table 1: Classification and Results NDVI in the Study Area

	Water, Snow, Cloud		Low Vegetation		Medium Vegetation		Dense Vegetation	
	0 <		0-0.2		0.2-0.4		> 0.4	
YEARS	Area(Km^2)	%	Area(Km^2)	%	Area(Km^2)	%	Area(Km^2)	%
2013	240.3	1.1	9283.7	43.7	10993.2	51.8	725.8	3.4
2017	237.5	1.1	9318.6	43.8	9152.3	43.1	2534.5	11.9
2021	159.8	0.8	14127.6	66.5	6557.2	30.9	398.4	1.9
2022	272.8	1.3	11074.5	52.1	8490.5	40.0	1405.4	6.6

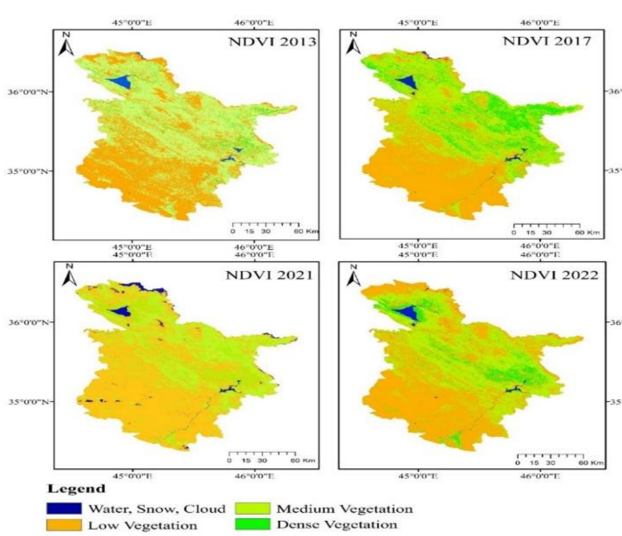

Figure 2: Normalized Difference Vegetation Index (NDVI) maps in Sulaymaniyah Province

3.2. Normalized Difference Water Index (NDWI)

The normalized difference to water index (NDWI) transformation was utilized to assess its correlation with drought probability. A lower NDWI value indicates drier conditions, while a higher NDWI value signifies wetter conditions. The study yielded NDWI values ranging from -0.3 to 0.776.

Among the results from Table 2 and Figure 3, the first class, Extremely Drought, recorded its highest area in the years 2017, 2021, and 2022, at a rate of 31.41%, 33.95%, and 34.77%. It occupied parts of the south and west of the study area, and the lowest area was in 2013, at a rate of 17.39%, which included parts of the southwest of the study area. As for the second severe drought class, it occupied 74.7% of the study area in the year 2013 for the southern parts, the area decreased in the years 2017 to 44.92% and then increased significantly in the southern parts for the years 2021 and 2022, to 60.9% and 57.28%. The third class, moderate drought, included the northern and eastern parts in 2013, with a percentage of 6.71%, then rose to 16% in 2017, then decreased to 3.77% in 2021, and it occupies separate areas in the study area, then increased in 2022 to reach 4.9% of the total area. The fourth class mild drought recorded 14.33% of the total area in the southern and southwestern parts of the study area. It decreased to 12.7% in the year 2017 and increased in 2021, reaching 3.77% in the northern parts, decreasing to 2.91% in the year 2022, as the fourth type, dry and moderate, occupied 0.57% of the total area in the northern and northeastern parts of the study area. It rose to 2.45% in the year 2017 and increased in 2021 and reached 3.77% in the northern parts, decreasing to 2.91% in 2022, which included the northern parts. As for the fifth class, no drought, it occupied the smallest area for all years and spread in the northern and northeastern parts of the study area. Areas with low NDWI values , as in the years 2017 and 2021, indicate areas vulnerable to drought conditions. These results agree with [8].

Table 2: Classifications and Results NDWI in the Study Area

	Extremely drought		Severely drought		Medium Vegetation		Moderately drought		No drought	
	0 <		0-0.2		0.2-0.3		0.3- 0.4		>0.4	
YEARS	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%
2013	3695.5	17.4	15869.6	74.7	1425.6	6.7	121.5	0.6	130.9	0.6
2017	6674.1	31.4	10604.9	44.9	3400.5	16.0	521.2	2.5	42.3	0.2
2021	7212.2	34.0	12937.2	60.9	801.9	3.8	191.9	0.9	99.7	0.5
2022	7386.2	34.8	12168.4	57.3	1042.7	4.9	619.8	2.9	26.3	0.1

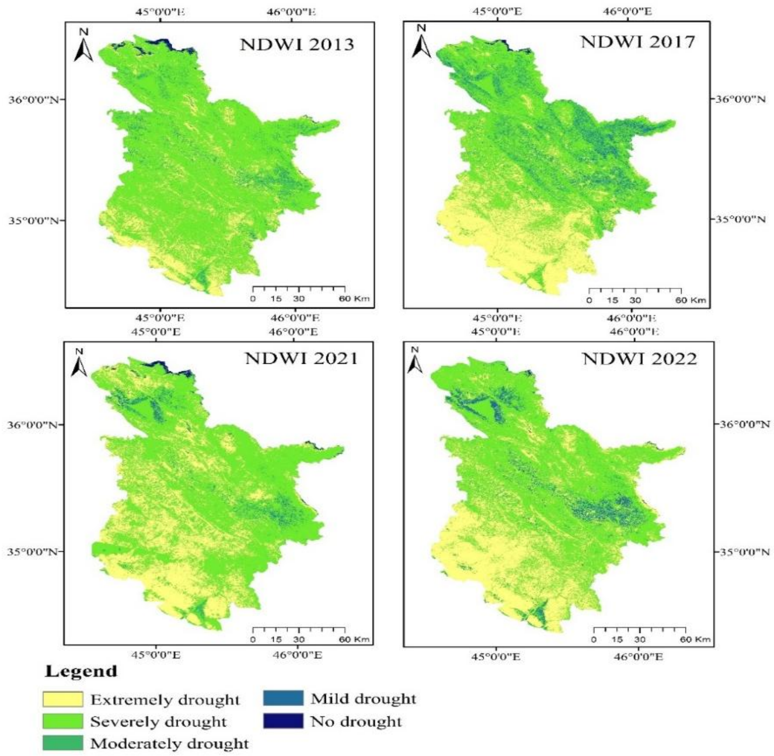

Figure 3: Normalized Difference Water Index (NDWI) maps in Sulaymaniyah Province

3.3 Normalized Drought Index (NDI):

The Normalized drought index increased in the southern part, while it decreased in the northern part. As a result, the northern part of Iraq is still not highly affected by climate change compared with other parts of Iraq. The NDI increased over time, from 0.42 in 2013 to 0.53 in 2022 as shown in Table 3), indicating a growing disparity between vegetation health and water availability, suggesting worsening drought conditions in Sulaymaniyah Governorate.

Table 3: Classifications and Results NDI in the Study Area

Year	$NDVI_{avg}$	$NDWI_{avg}$	NDI (Drought Coefficient)
2013	0.215	0.088	0.421
2017	0.232	0.084	0.47
2021	0.168	0.059	0.481
2022	0.204	0.063	0.529

Conclusion

The analysis of NDVI and NDWI data from 2013 to 2022 reveals a deteriorating drought situation in Sulaymaniyah Governorate. Vegetation health has declined, as evidenced by the increase in low vegetation areas and the decrease in dense vegetation areas. The extent of drought-affected areas has also grown, as shown by the rising NDI values. NDVI data indicate that low vegetation dominated the region, peaking in 2021 at 66.5%, up from 43.7% in 2013, before falling to 39.97% in 2022. Medium vegetation reached its highest point in 2013 at 51.75%, but declined in subsequent years, while dense vegetation was most prominent in 2017. NDWI data show that severe drought covered 74.7% of the area in 2013, decreased to 44.92% in 2017, and then surged to 60.9% in 2021 and 57.28% in 2022. These findings highlight that drought patterns varied across the region, with the southern and southwestern areas being most affected in 2017, 2021, and 2022. The increase in NDI values from 0.42 in 2013 to 0.53 in 2022 underscores the growing gap between vegetation health and water availability, pointing to increasingly severe drought conditions in Sulaymaniyah Governorate.

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تغير استخدامات الأراضي وتأثيراته على ديناميكيات الجفاف في محافظة السليمانية خلال الفترة من 2013 إلى 2022.

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الخلاصة

يعد الجفاف ظاهرة بارزة مرتبطة بتغير المناخ، تؤثر على قطاعات مختلفة. يعتبر التخطيط الفعّال أمرًا ضروريًا للتخفيف من آثاره وتقليل الأضرار المحتملة. تم استخدام بيانات الاستشعار عن بُعد والتحليل المكاني القائم على نظم المعلومات الجغرافية *(GIS)* لتقييم ظروف الجفاف. تركز هذه الدراسة على محافظة السليمانية، الواقعة في شمال شرق العراق، وتغطي مساحة تبلغ 21,240 كم². تقع المحافظة جغرافيًا بين خطي طول 44°49'59" شرقًا و45°59'43" شرقًا، وخطي عرض 34°21'07" شمالًا و36°15'48" شمالًا. استخدمت الدراسة بيانات القمر الصناعي *Landsat 8 OLI* لاستخلاص مؤشرين طيفيين رئيسيين: مؤشر اختلاف الغطاء النباتي الطبيعي *(NDVI)* ومؤشر اختلاف المائي الطبيعي *(NDWI)*. تم تحليل هذه المؤشرات باستخدام برنامج *ArcGIS 10.4.1* لتقييم ظروف الجفاف وتوزيعها المكاني في المنطقة. وتم إعداد خرائط تبرز قيم *NDVI*و *NDWI*لتقييم تأثيرات الجفاف للأعوام 2013، 2017، 2021، و2022. تشير النتائج إلى وجود تباين مكاني واضح في شدة الجفاف عبر المحافظة. يُظهر تحليل *NDVI* للفترة من 2013 إلى 2022 تقلبات ملحوظة في الغطاء النباتي، حيث ارتفعت نسبة الغطاء النباتي الضعيف من 43.7٪ إلى 66.5٪ في عام 2021، في حين بلغت نسبة الغطاء النباتي الكثيف ذروتها عند 11.9٪ في عام 2017 قبل أن تنخفض بشكل حاد. كما يُظهر تحليل *NDWI* زيادة في المناطق المتأثرة بشدة بالجفاف من 17.4٪ إلى 34.8٪، بينما انخفضت المناطق الخالية من الجفاف من 0.6٪ إلى 0.1٪. تعكس هذه النتائج تزايد الجهد المائي والتغيرات البيئية في محافظة السليمانية. بعد عام 2017 انخفضت كثافة الغطاء النباتي وازدادت حدة الجفاف كما ارتفع مؤشر الجفاف الطبيعي *(NDI)* من 0.42 في عام 2013 إلى 0.53 في عام 2022، مما يشير إلى اتساع الفجوة بين صحة النباتات وتوافر المياه، في دلالة على تفاقم ظروف الجفاف في محافظة السليمانية.

الكلمات المفتاحية: الجفاف، السليمانية، مؤشر الفرق المعياري للغطاء النباتي *(NDVI)*، مؤشر فرق المياه الطبيعي *(NDWI)*، نظم المعلومات الجغرافية *(GIS)*.