



RESEARCH ARTICLE



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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 Geographic Information System (GIS)-based spatial analysis were employed to assess drought conditions. This study focuses on Sulaymaniyah Province, located in northeastern Iraq, covering an area of 21,243 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 9283.7 km² (43.7%) in 2013 to 14127.6 km² (66.5%) in 2021 and dense vegetation peaking at 2534.5 km² (11.9%) in 2017 before declining sharply. NDWI analysis indicates a rise in extremely drought-affected areas from 3695.5 km² (17.4%) in 2013 to 7386.2 km² (34.8%), in 2022 while no-drought zones decreased from 130.9 km² (0.6%) in 2013 to 26.3 km² (0.1%) in 2022. These findings reflect increasing water stress and environmental changes in Sulaymaniyah Governorate. Vegetation density declined after 2017, and drought severity worsened. Normalized Differences Drought Index (NDDI) increased from 0.421 in 2013 to 0.529 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.

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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 Sulaymaniyah 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 km². 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 United State Geological Survey (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.

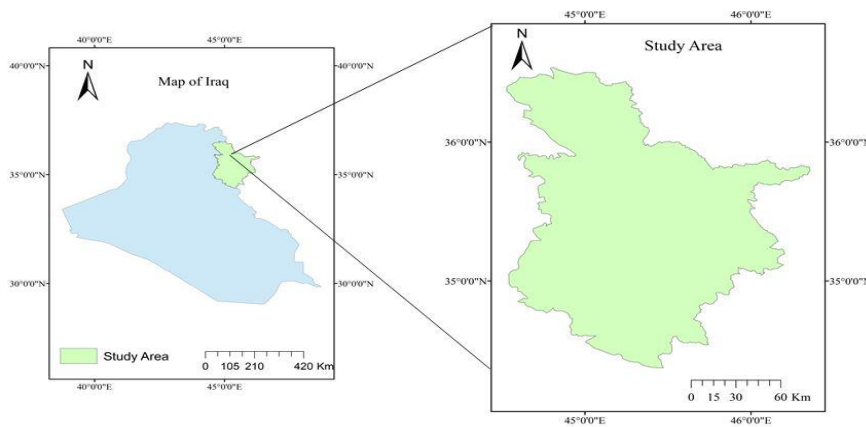


Figure 1: Study Area and Geographical map of Sulaymaniyah Province, Iraq [Authors]

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]. Equation 1 show the NDVI algorithm.

$$NDVI = \frac{NIR(B5) - Red(B4)}{NIR(B5) + Red(B4)} \dots\dots\dots (1) [21]$$

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 [22] and [23]. 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 [24]. By combining NIR

and SWIR bands, NDWI enhances accuracy by accommodating differences in internal leaf structure and dryness [25]. Equation 1 show the NDWI algorithm.

$$NDWI = \frac{NIR(B5) - SWIR(B6)}{NIR(B5) + SWIR(B6)} \dots\dots\dots (2) [26]$$

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. The indices of NDVI and NDWI were analyzed using ArcGIS 10.4.1.

2.4. Normalized Differences Drought Index (NDDI):

The Normalized Differences Drought Index (NDDI) 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 NDDI indicates better vegetation health relative to available water, while a lower NDDI suggests increasing drought severity.

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

$$NDDI_{Avg} = \frac{NDVI_{avg} - NDWI_{avg}}{NDVI_{avg} + NDWI_{avg}} \dots\dots\dots (3) [27]$$

$$NDVI_{Avg} = \frac{Weighted\ Sum}{Total\ area} \dots\dots\dots (4)$$

$$NDWI_{Avg} = \frac{Weighted\ Sum}{Total\ area} \dots\dots\dots (5)$$

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, and based on the Normalized Difference Vegetation Index, which categorizes vegetation density into four classes—no vegetation represented by water, snow, cloud (0>), low vegetation (0–0. 2), medium vegetation (0. 2–0. 4), and dense vegetation (>0. 4). The prevalence of the low vegetation type in all years and the lowest area was recorded in 2013 at 9283.7 km² (43.7%), then rose slightly to reach 9318.6 km² (43.8%) in 2017, then it rose to its highest level in 2021 which reached to 14127.6 km² (66.5%), its area will then decrease to 11074.5 km² (52.1%). As for the medium vegetation type, its highest area was recorded in 2013 at 10993.2 km² (51.8%), then it decreased during subsequent years to 9152.3 km² (43.1%), 6557.2 km² (30.9%), and 8490.5 km² (40.0%) for the years 2017, 2021, and 2022, respectively. As for the dense vegetation type, it constituted the smallest area for all years of the study, in 2013 the occupied area was 725.8 km² (3.4%), then rose to the highest level with area of 2534.5 km² (11.9%) in 2017, then decreased to the lowest area since the study years in 2021 with area of 398.4 km² (1.9%), to raise that to 1405.4 km² with (6.6%) in 2022 . 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 [Autthers]

YEARS	Water, Snow, Cloud		Low Vegetation		Medium Vegetation		Dense Vegetation	
	0 >		0-0.2		0.2-0.4		> 0.4	
	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

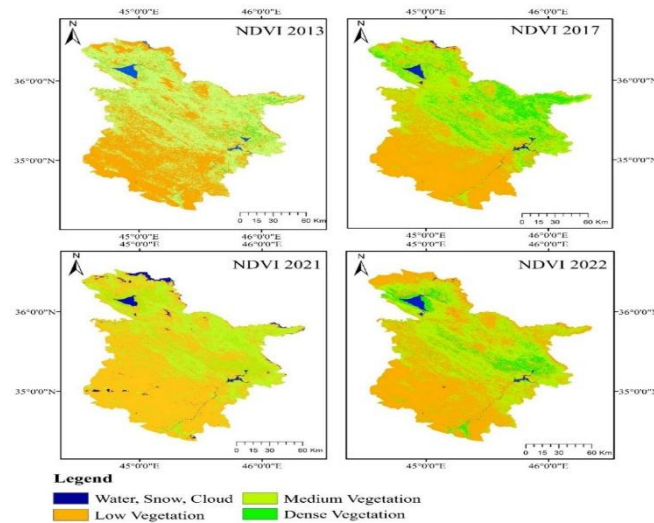


Figure 2: Normalized Difference Vegetation Index (NDVI) maps in Sulaymaniyah Province [Authers]

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.

From the results of table 2 and figure 3, and based on the Normalized Difference Water Index, which categorizes drought conditions into five classes—extreme drought (<0), severe drought (0–0. 2), moderate drought (0. 2–0. 3), mild drought (0. 3–0. 4), and no drought (>0. 4)—the table shows drought conditions in the study area. The amount of extreme drought has clearly increased throughout time, from 3,695. 5 km² (17. 4%) in 2013 to 6,674. 1 km² (31. 4%) in 2017, 7,212. 2 km² (34. 0%) in 2021, and 7,386. 2 km² (34. 8%) in 2022, pointing to more severe aridity. The study area is consistently dominated by severe drought, which covered 15,869. 6 km² (74. 7%) in 2013, then shrank to 10,604. 9 km² (44. 9%) in 2017, before expanding once more to 12,937. 2 km² (60. 9%) in 2021 and somewhat decreasing to 12,168. 4 km² (57. 3%) in 2022. Moderately drought fluctuates greatly, rising from 1,425. 6 km² (6. 7%) in 2013 to 3,400. 5 km² (16. 0%) in 2017 before falling sharply to 801. 9 km² (3. 8%) in 2021 and 1,042. 7 km² (4. 9%) in 2022. The mild drought continues to be localized, covering 121. 5 km² (0. 6%) in 2013, 521. 2 km² (2. 5%) in 2017, 191. 9 km² (0. 9%) in 2021, and 619. 8 km² (2. 9%) in 2022. Drought conditions are at a minimum overall year, with 130. 9 km² (0. 6%) in 2013, 42. 3 km² (0. 2%) in 2017, 99. 7 km² (0. 5%) in 2021, and 26. 3 km² (0. 1%) in 2022. In general, the data demonstrate that the study region is dominated by severe and extreme drought categories, while the areas experiencing no or moderate drought are still quite limited. This emphasizes the ongoing and growing severity of the drought over time. These results agree with [8].

Table 2: Classifications and Results NDWI in the Study Area [Authers]

YEARS	Extremely drought		Severely drought		Moderately drought		Mild drought		No drought	
	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

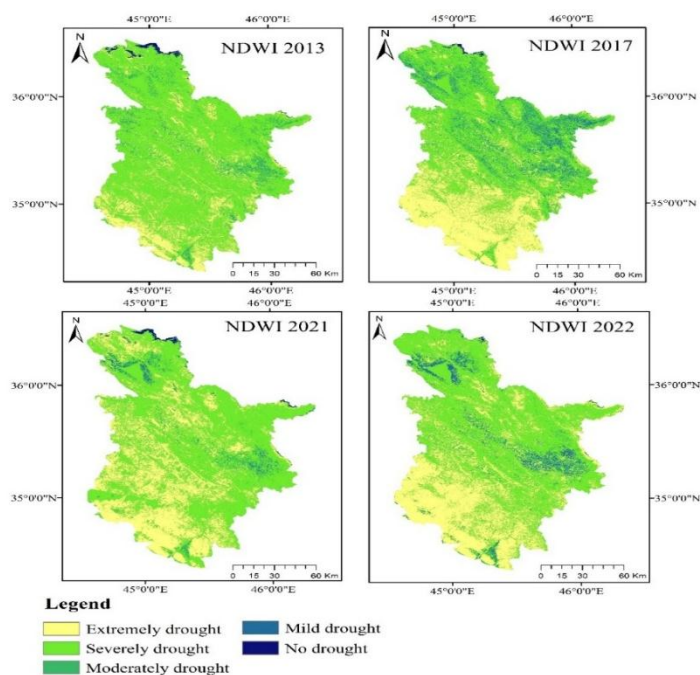


Figure 3: Normalized Difference Water Index (NDWI) maps in Sulaymaniyah Province [Authors]

3.3 Normalized Differences Drought Index (NDDI):

The Normalized differences 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 NDDI increased over time, from 0.421 in 2013 to 0.529 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 of NDDI in the Study Area [Authors]

Year	NDVI _{avg}	NDWI _{avg}	NDDI (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 of years 2013, 2017, 2021 and 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 NDDI values. NDVI data indicate that low vegetation dominated the region, peaking in 2021 at 14127.6 km² (66.5%), up from 9283.7 km² (43.7%) in 2013, before reaching 11074.5 km² (52.1%) in 2022. Medium vegetation reached its highest point in 2013 at 10993.2 km² (51.8%), but declined in subsequent years. NDWI data show that severe drought covered an area of 15869.6 km² (74.7%) in 2013, then decreased to 10604.9 km² (44.9%) of the area in 2017, and then surged to 12937.2 km² (60.9%) in 2021 and 12168.4 km² (57.3%) 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 NDDI 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.

References

- [1]. Rhee, J.; Im, J. and Carbone, G.J. 2010, Monitoring Agricultural Drought for Arid and Humid Regions Using Multi-Sensor Remote Sensing Data. *Remote Sens. Environ.*, 114, 2875-2887.
- [2]. Mohammed, F. O., Mohammad, A. O., Ibrahim, H. S., & Hasan, R. A. (2021). Future Scenario of Global Climate Map Change according to the Köppen-Geiger Climate Classification. *Baghdad Science Journal*, 18(2 (Suppl.)), 1030–1030.

- [3]. Hirche, A.; Salamani, M.; Abdellaoui, A.; Benhouhou, S. and Valderrama, J.M. 2011, Landscape Changes of Desertification in Arid Areas: The Case of South-West Algeria." *Environ Monitoring Assess* 179, 403-420.
- [4]. [Ali, D.A.; Abdulrahman, N.M. and Rahem, B.R. 2023, Some Heavy Metals Status and Water quality parameters of Darbandikhan Dam, Sirwan and Tanjaro rivers. *Kirkuk University Journal for Agricultural Sciences*, 14, 131-150.
- [5]. Jasim, A. I., & Awchi, T. A. (2020). Regional meteorological drought assessment in Iraq. *Arabian Journal of Geosciences*, 13(7), 284.
- [6]. Hedres, I.H.; Khalaf, A.A. and Shihab, M.R. 2022, Using of SEBAL model for estimating net solar radiation and land surface temperature in the Dyala River Basin. *Kirkuk University Journal for Agricultural Sciences*, 13,48-61.
- [7]. Amalo L.F.; Hidayat, R. and Sulma, S. 2018, Analysis of agricultural drought using vegetation health index. *Journal of Agricultural Science*, 40, 63-73.
- [8]. Hamed, M. M., Sammen, S. S., Nashwan, M. S., & Shahid, S. (2023). Spatiotemporal variation of drought in Iraq for shared socioeconomic pathways. *Stochastic Environmental Research and Risk Assessment*, 37(4), 1321–1331.
- [9]. Tucker, C.J. 1979, Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sens. Environ*, 8, 127-150.
- [10]. Peters, A.J.; Elizabeth, A.; Walther-Shea, L.J.; Vina, A.; Hayes, M. and Svoboda, M.D. 2002, Drought Monitoring with NDVI-Based Standardized Vegetation Index. *Photogrammetric Engineering & Remote Sensing*, 68, 71-75.
- [11]. McFeeters, S.K. 1996, The use of the normalized Difference Water Index (NDWI) in the delineation of open water features. *Int. J. Remote Sensing* 17, 1425-1432.
- [12]. Gao, B.C. 1996, NDWI A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sens. Environ*, 58, 257-266.
- [13]. Zhang, N.; Hong, Y.; Qin, Q. and Zhu, L. 2013, Evaluation of the visible and shortwave infrared drought index in China *Int. J. Disaster Risk Sci.* 4, 68-76.
- [14]. Ali, K.D. 2024, Geospatial Technique Applications in Groundwater Investigation. *Kirkuk University Journal for Agricultural Sciences*, 15, 91-97.
- [15]. Younis, M.S. and Moustafa, S.M. 2018, Biodiversity Mix Natural Forest Distribution in Qara Mountain Region. *Kirkuk University Journal for Agricultural Sciences*, 9, 107-116.
- [16]. Yang, Y.; Wu, T.; Wang, S.; Li, J. and Muhammad, F. 2019, The NDVI-CV Method for Mapping Evergreen Trees in Complex Urban Areas using Reconstructed LANDSAT 8 Time-Series Data. *Forests*, 10, 139-149.
- [17]. Mishra, A.K.; Ines, A.V.; Das, N.N.; Khedun, C.P.; Singh, V.P.,; Sivakumar, B. and Hansen, J.W. 2015, Anatomy of a local-scale drought: Application of assimilated remote sensing products, crop model, and statistical methods to an agricultural drought study. *Journal of Hydrology*. 526, 15-29.
- [18]. Najmaddin, P.M.; Whelan, M.J. and Balzter, H. 2017, Estimating daily reference evapotranspiration in a semi-arid region using remote sensing data, *Remote Sensing*, 779, 1-20.
- [19]. Al-Quraishi, A. M. F., Qader, S. H., & Wu, W. (2019). Drought monitoring using spectral and meteorological based indices combination: A case study in Sulaimaniyah, Kurdistan region of Iraq. In *Environmental remote sensing and GIS in Iraq* (pp. 377–393). Springer. https://link.springer.com/chapter/10.1007/978-3-030-21344-2_15
- [20]. Pirotti, F.; Parraga, M.A.; Stuardo, E.; Dubbini, M.; Masiero, A. and Ramanzin, M. 2014, NDVI from Landsat 8 Vegetation Indices to Study Movement Dynamics of Capra ibex in Mountain Areas. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* 40, 147-153.
- [21]. Rouse, J. W.; R. H. Haas; A. Schell and D. W. Deering. 1974. Monitoring vegetation systems in the Great Plains with ERTS. In: *Third Earth Resources Technology Satellite-1 Symposium, Volume I: Technical Presentations*. Freden, S.C, Mercanti, E.P., Becker, M.A. (Eds.). Washington, D.C.: NASA SP-351, 309–317.
- [22]. Spadoni, G.L.; Cavalli, A.; Congedo, L. and Munafo, M. 2020, Analysis of Normalized Difference Vegetation Index (NDVI) Multi-Temporal Series for the Production of Forest Cartography. *Remote Sens. Appl. Soc. Environ.* 20, 20-33.
- [23]. Andana, E.K. 2015, Pengembangan Data CitraSatelit Landsat 8 Untuk Pemetaan Area Tanaman Hortikultura Dengan Berbagai Metode Algoritma Indeks Vegetasi (Studi Kasus: Kabupaten Malang Dan Sekitarnya). *Nas. Manaj. Teknol*, 9, 1-10.
- [24]. Zeng, L.; Wardlow, B.D.; Xiang, D.; Hu, S. and Li, D. 2020, A Review of Vegetation Phenological Metrics Extraction Using Time-Series, Multispectral Satellite Data. *Remote Sens. Environ*, 237, 1-47.
- [25]. Sánchez-Ruiz, S.; Piles, M.; Sánchez, N.; Martínez-Fernández, J.; Vall-llossera, M. and Camps, A. 2014, Combining SMOS with Visible and Near/Shortwave/Thermal Infrared Satellite Data for High Resolution Soil Moisture Estimates. *J. Hydrol.* 516, 273-283.
- [26]. Gao, B.C. 1996. NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sensing of Environment*, 58, 257-266
- [27]. Charat M, Wattanakij N, Kamchai T, Mongkolsawat K and Chuyakhai D 2009 Exploration of Spatio-Temporal Drought Patterns Using Satellite-Derived Indices for Crop Management in Northeastern Thailand. (Beijing: Asian association on remote sensing).

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 الفعال أمراً ضرورياً 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 جغرافياً بين خطي طول 44°49'59" شرقاً و 45°59'43" شرقاً، وخطي عرض 34°21'07" شمالاً و 36°15'48" شمالاً. 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، و 2022. 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 9283.7 km² (43.7%) في 2013 إلى 14127.6 km² (66.5%) في عام 2021، في حين بلغت نسبة الغطاء النباتي الكثيف ذروتها عند 2534.5 km² (11.9%) في عام 2017 قبل أن تنخفض بشكل حاد. كما يُظهر تحليل NDWI زيادة في المناطق المتأثرة بشدة بالجفاف من 3695.5 km² (17.4%) في 2013 إلى 7368.2 km² (34.8%) في 2022، بينما انخفضت المناطق الخالية من الجفاف من 130.9 km² (0.6%) في 2013 إلى 26.3 km² (0.1%) في 2022. تعكس هذه النتائج تزايد الجهد المائي والتغيرات البيئية في محافظة السليمانية. بعد عام 2017 انخفضت كثافة الغطاء النباتي وازدادت حدة الجفاف كما ارتفع مؤشر اختلاف الجفاف الطبيعي (NDDI) من 0.42 في عام 2013 إلى 0.529 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).