ISSN 2303-4521
Periodicals of Engineering and Natural Sciences *Original Research*
Vol. 11, No. 1, February 2023, pp.47-63

Monthly drought monitoring of the surface water area of Sawa Lake, Iraq during 2016-2022 using remote sensing data

Lubna Alshammari[1], Omar Natiq Mohammed[2],
[1] Civil Engineering Department, Faculty of Engineering, Al-Mustansiriyah University, Baghdad, Iraq
[2] Nudhum Al-Omran Company for Consultancy Services, Baghdad, Iraq

ABSTRACT

Drought is a common phenomenon in Iraq's environment, and the country has experienced severe drought events exacerbated by the threat of climate change (low rainfall and high temperatures) over the past two decades. Iraq is located in a semi-arid region whose water resources have been restricted and mostly shared with its neighbours. To investigate the effect of drought on the surface water area of Sawa lake, we analysed 52 Sentinel-2 images from May 2016 to July 2022 using an open-source SNAP toolbox to map the boundary of the surface-water body of the lake. The results indicate that the surface water area of Sawa lake has decreased significantly over the last six years with the most extreme decline beginning in May 2021, when the area of the lake lost about 51% of its initial size (May 2016). By March 2022, the lake had disappeared and about 96% of the water's surface area had been lost. To better understand the potential causes of droughts, further analysis has been conducted on the effects of precipitation and human activities (vegetation cover and Al-Samawah saltpan for salt production) on the lake. Investigations revealed that the rapid expansion of agricultural areas around the lake by 254% and the increase in salt production from the Al-Samawah saltpan by about 121% are among the direct causes of the drought. In addition, the results of the statistical test analysis between the estimated surface water area of Sawa lake and human activities were significant at a 95% level of confidence. The findings of this study can assist decision-makers to understand the interaction between human activities and the lake's environment to design a strategic plan for lake recovery and a sustainable water resource management system in southern Iraq.

Keywords: Sawa lake; drought; monthly monitoring, surface water, sustainable water resource

Corresponding Author:

Lubna Alshammari
Civil Engineering Department, Faculty of Engineering,
Al-Mustansiriyah University,
Baghdad, Iraq
Email: Lubna.alshammari@uomustansiriyah.edu.iq

1. Introduction

Drought is one of the most significant natural disasters, affecting water resources, agricultural productivity, ecosystems, human health, and the global economy [1-3]. Many regions around the world are anticipated to experience increasingly extreme and frequent drought events as a result of global warming [4]. The impacts of drought have been noticeable on surface water resources, which are already at risk from massive withdrawals due to growing demand, lack of conservation and unsustainable land management [5]. In addition, droughts have a severe negative impact on agriculture, the environment and socio-economic sectors [6]. Effective spatial and temporal drought monitoring is thus required to mitigate these effects.

Drought is primarily caused by low precipitation rates; however, human, and social activities can contribute to drought. [7, 8]. In Iraq, the drought situation has been reported by several researchers [9]. According to the Iraqi report issued in 2009 by the Coordination of Humanitarian Affairs and the United Nations Assistance Mission in Iraq, the key factors to the recurrence of drought episodes in Iraq include low precipitation and low water discharge rates in the main rivers [6]. As a result, this causes a decrease in groundwater levels, rivers flow, and the drying up of water sources (springs, deep wells and shallow wells) [10]. Due to Iraq's position in arid and semi-arid zones, droughts have occurred frequently during the past two decades. In the majority of North African and West Asian countries, low precipitation and seasonal variations are typical. This places Iraq, along with other countries, in a position where important drought management measures are required. [11].

The monitoring of drought on a spatial and temporal scale is a complicated procedure that has been developed over several decades [12, 13]. Indicators of drought, such as water anomalies, are used to monitor and identify droughts and other conditions that result in a lack of available water [13]. Using these indicators, one can assess the Spatio-temporal degree of drought as well as the severity (roughness) of the conditions [14]. Drought-related hazards can have an impact on hydrological components over a wide range of spatial and temporal scales [12].

In terms of platforms, satellite remote sensing plays a key role in identifying, mapping, analyzing and tracking drought and its effects on surface water resources and vegetation cover, particularly for large areas with limited resources for in-situ measurements as this method is affordable and repeatable. Different types of Remote Sensing optical images (with very high, high and medium spatial resolution) have been used to monitor the drought of the inland surface water bodies. Maps of inland water bodies extracted from very high-resolution satellite images have a fine spatial resolution [15, 16], however, data acquisition is expensive and may not be sufficient to monitor the long-term dynamic of water bodies [17]. The Medium Resolution Imaging Spectroradiometer (MODIS) has frequent coverage, which provides the opportunity for dynamic monitoring every few days, but the spatial resolution of 250 m is too coarse, especially for detecting subtle changes in inland water bodies. High-resolution remote sensing (HR) multispectral satellite images balance the spatial resolution and temporal frequency [18] and have been widely used because these images provide the following advantages: spectral data on water properties, suitable spatial resolution (tens of meters), frequent monitoring (every nearly half a month), large scale coverage, and free access.

There are several indicators in the study of drought using remote sensing data. These indicators compare the low reflectance of water with the higher reflectance of different types of land cover through infrared channels. Water indices can be used to estimate the surface water areas, which are derived using two or more bands to discriminate between water and land characteristics [19, 20]. Over the last few decades, numerous water and vegetation indices have been created and utilized in various modifications, combinations, and methodologies, including Normalized Difference Water Index (NDWI) [21], Modified Normalized Water Index (MNDWI) [22], Automated Water Extraction Index (AWEI) [23], and Normalized Difference Vegetation Index (NDVI) for monitoring drought on vegetation [24]. Based on the derived land-water indexes, the more difficult task is the separation between land and water in optical imagery. Therefore, in this study, we combined four water indices to identify the water bodies based on their respective strengths and used one index for evaluating the vegetation cover.

In Iraq, great efforts have focused on monitoring the impact of drought on surface water bodies and vegetation cover by extracting annual changes of surface water areas and vegetation cover at large scales using Landsat images [6, 25, 26]. However, inland water bodies, especially ephemeral streams and lakes are subject to dynamic changes and severe drainage. In addition, in some regions around lakes (e.g., Sawa lake; the study area), agricultural lands are expanding, resulting in an increase in the seasonal demand for agricultural water. Furthermore, the Badia region close to Sawa lake is home to several different industrial zones, such as Al-Samawah saltpan for salt production. This process also requires large amounts of groundwater, leading to additional stress on the surface water body of the lake. One of the most important aspects of the sustainable water management system for Sawa lake is gaining an understanding of the dynamics of the lake as well as the influence that human activities have on it. Thus, monitoring with higher temporal and spatial resolution, such as the use of monthly analysis with a resolution of 10 m, can better capture interannual and seasonal changes in surface water extent and understand the relationship between surface water area change and key driving factors behind the drought. To our knowledge, this research is the first to use satellite imagery for monthly drought monitoring of the surface water of Sawa lake in Iraq. Accordingly, the study uses Sentinel- 2 data to achieve this goal. The main contributions are to propose an accurate approach for determining the extent of surface water bodies and the vegetation cover and monthly evaluating its change, identification of the most affected areas (spots with considerable change) and evaluating the impact of both climate change by means of rainfall and human activities on the drought of the lake.

2. Materials and methods

2.1. Sawa Lake

Sawa lake is located in the western part of the Mesopotamian Plain in Iraq, close to the border with Western Sahara [25]. It is positioned around 23 kilometres west of Samawah City between the coordinates 497960 E-505620 E and 3466670 N -3461420 N (WGS-1984-UTM-Zone-38N) (Figure 1). The lake is composed of limestone rocks, with gypsum forming its border. It is distinguished by its unique water chemistry, and its salt content is much higher than that of the Arabian Gulf [27].

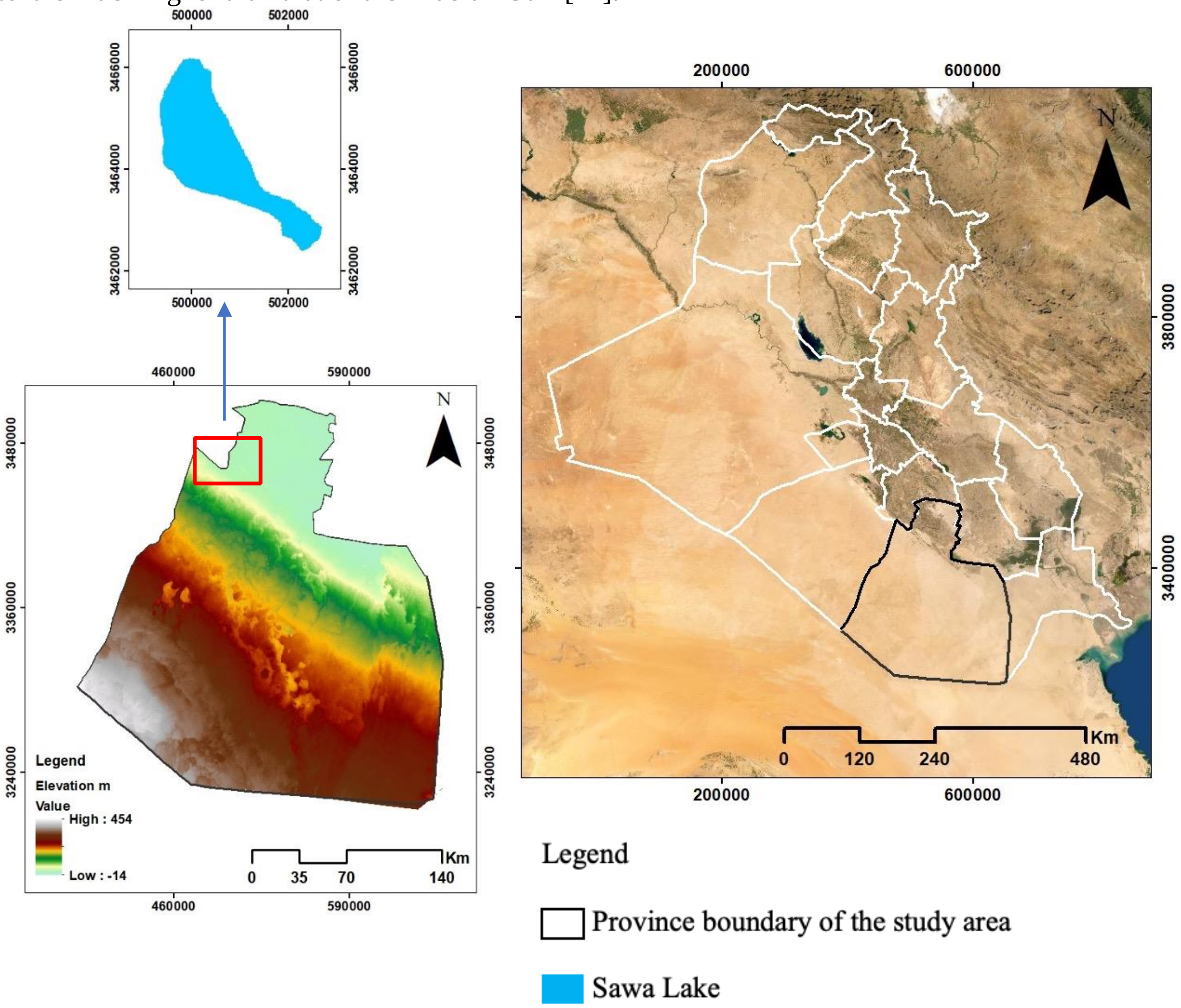

Figure 1. The location of the study area with the Digital Elevation Model (DEM)

Sawa lake is recognized as of international importance and listed by UNESCO in 2014. It is considered as being among the most significant permanent water bodies in the region [28]. Due to the existence of a large number of morphological characteristics, the lake is pointed to be one of the most significant Ramsar water bodies in Iraq.

The main feature of the lake is a permanent and closed water body, without obvious water resources in the surrounding region. The groundwater resources (such as springs and sinkholes) represent the primary source of the water supply to the lake and the Dammam aquifers constitute the main source of water supply through a network of joints or faults [29]. Another interesting feature of Sawa lake is that it has a water level that is about 2 meters higher than the topography that surrounds it (particularly to the southwest) and about 5 meters higher than the Euphrates [28]. Finally, Sawa lake has a unique equilibrium system. For example, there is no substantial rise in salt concentration (Sodium) despite the considerable reduction in water level (from 5 meters to 1.5 meters). A drop in the water level should cause a considerable rise in the sodium content, however, this is not the case. In contrast, the increase in sodium content neglects the decrease in groundwater depth and the increase in spring water inflow (sinkholes). Consequently, it is assumed that the lake has a remarkable water recycling (washing) system, which may represent the second reason for the decrease in water and evaporation.[30]. All of these components contribute to the Sawa lake features to meet all four natural criteria for outstanding global qualities needed for inclusion in the World Natural Heritage List [28].

Recently, Natural pasturelands near Sawa lake have been replaced by agricultural lands. Both pasture and agricultural lands depend mostly on the seasonality of rainfall. The conversion of pastures into agricultural lands is managed by the local government and the investment authority of the local governorate, and this is achieved by granting legal investment licenses to investors. These agricultural areas are used for production and delivery to both domestic and international consumers. Most of the agricultural areas have been planted with strategic crops after the preparation of the ground and the digging of artesian wells. The agricultural investment aims to increase agricultural output, diversify revenue streams for local farmers, and develop work opportunities for the province's residents. These were the major forces for the rise in agricultural areas in the Badia region after 2010 [25].

In addition, in the southeastern part of Sawa lake, there is an artificial salt lake called the Al-Samawah saltpan. This lake produces sodium chloride (NaCl) through the evaporation process of water in multiple pools. In 2016, Al-Samawah saltpan initiated a development plan intending to increase the production capacity of salt to a design capacity of 500,000 tons/year. The plan was successfully carried out in 2019 by raising the groundwater pumping to 500 m3/hr discharge [26].

The high demand for groundwater for agricultural and industrial purposes has increased the water pressure on the lake as well as the effect of climate change (lower rainfall and higher temperatures) and water shortage making it an interesting lake that requires detailed analysis.

2.2. Remote sensing data

In this study, satellite images obtained by the Sentinel-2 sensor were used. These images were downloaded from the open-access Copernicus Hub (https://scihub.copernicus.eu/ accessed on 6 August 2022). The Sentinel-2 mission is made up of a two-satellites system: Sentinel-2A and Sentinel-2B. These satellites were launched in June 2015 and March 2017, respectively. This allows for a high temporal frequency of up to approximately 10 days for one Sentinel-2 satellite, and 5 days for a combined constellation [31]. For dynamic monitoring of surface water bodies and vegetation cover, a high revisit frequency is essential. Sentinel-2 is equipped with a Multispectral Imager (MSI) that provides 12 spectral bands spanning in a spatial resolution from 10 m to 60 m and covering visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) bands [32]. In this study, six broad bands, including the VIS, NIR, and SWIR bands are utilized (Table 1). Two types of Sentinel-2 products were used: Level-1C which is created systematically from the mission’s start and requires radiometric correction, and Level-2A which is atmospherically and radiometrically corrected, and this Level started worldwide coverage by the beginning of 2019. Therefore, all Sentinel-2 images obtained before 2019 were radiometrically corrected before processing.

Table 1. Information of the used bands of Sentinel-2 data

Band Number	Band Name	Resolution
B2	Blue	10
B3	Green	10
B4	Red	10
B8	NIR	10
B11	SWIR 1	20
B12	SWIR 2	20

To analyse Sawa lake, 52 Sentinel-2A images were acquired for each month (with some data gaps) for the monitoring period of May 2016 and July 2022 (Table 2). These images cover the four seasons (starting on 1st December, 1st March, 1st June, and 1st September for winter, spring, summer and autumn respectively) during a six-years period. The same images were used to estimate the vegetation cover and the surface water area of Al-Samawah Saltpan near Sawa lake.

Table 2. Summary of the images used for monthly monitoring of surface water body and vegetation cover of the study area.

Sensor	Monitoring Period	Number of Images Used	Utilization
Sentinel-2	May 2016 - July 2022	25 images Level-1C	To extract surface water area and vegetation cover
		27 images Level-2A	

2.3. Rainfall and temperature data

The estimation of the rainfall ratio is critical for understanding how climate change affects the area. This might be another factor contributing to the deterioration of the lake. The NASA Prediction of Worldwide Energy Resources was used to determine the quantity of rainfall in the study area. (https://power.larc.nasa.gov/data-access-viewer/ accessed on 16 July 2022).

2.4. Methodology

The applied methodology in this study is divided into three major parts (Figure 2): Remote Sensing data used as input data, pre-processing, and the processing steps. The input data included Sentinel-2 images. Sentinel-2 Level-1C products have been atmospherically and radiometrically corrected using the "Sen2Cor" processor in the ESA (European Space Agency) Sentinel Application Platform (SNAP) toolbox [33]. Then all Sentinel-2 images were passed through resampling and subset. Subsequently, the water surface of the lakes and vegetation cover were extracted. The verification procedure was conducted using the Google Earth images archive. Finally, a statistical test analysis was conducted to identify any correlation that may have contributed to the drought of Sawa lake.

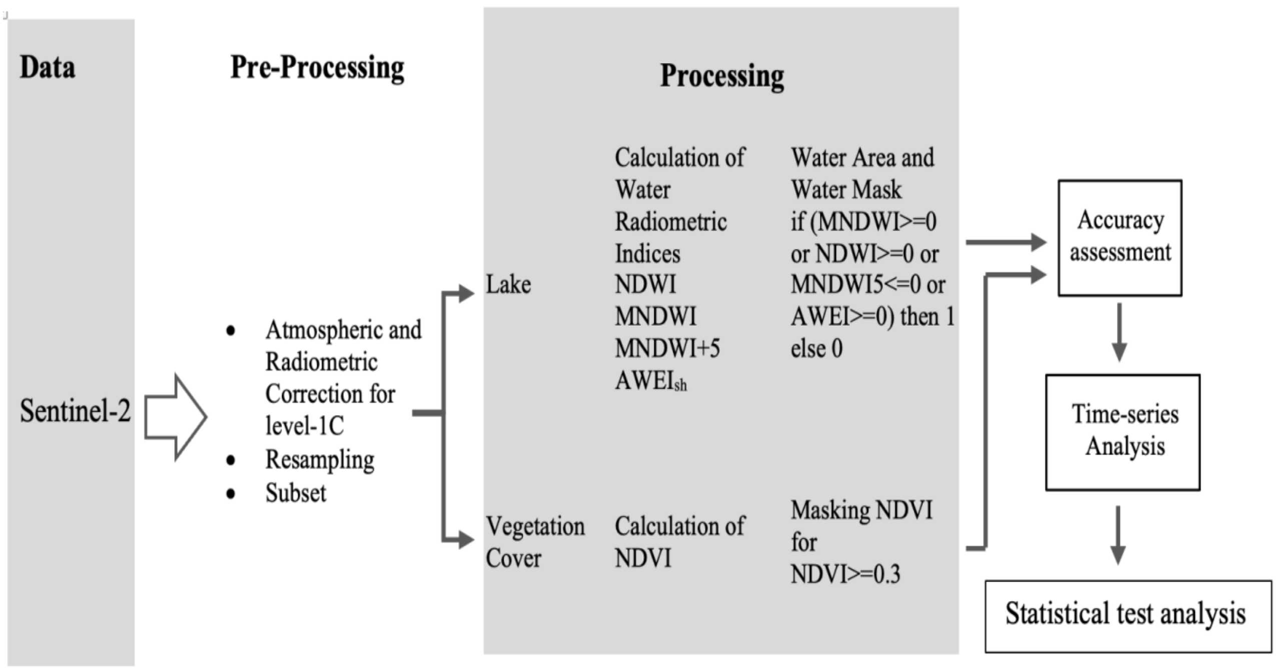

Figure 2. Flowchart illustrating the applied methodology

2.5. Calculation of surface water area and vegetation cover using Sentinel-2 data

2.5.1. Surface water area extraction

As mentioned previously, images from Sentinel-2 Level-1C required atmospheric correction, which was performed in the SNAP toolbox. Then resampling process by using a reference band was conducted for all images to make them have the same spatial resolution which is 10m. The next step was to subset all images to the area of interest and keep only the bands that will be used in the analysis (Table 1).

In recent decades, several water indices for identifying water bodies have been developed. However, there is no ideal water index that works in all regions. Particularly close to shore, water indices react with a particular degree of sensitivity [31]. All water indices are developed to separate water and land pixels as good as possible. Therefore, the combination of four water indices[34] was used to identify the water bodies based on their respective strengths. These indices are the Normalized Difference Water Index NDWI, Modified Normalized Water Index MNDWI, Modified Normalized Difference Water Index VI (MNDWI+5), and Automated Water Extraction Index for shadow area $AWEI_{sh}$.

- NDWI

Normalized Difference Water Index NDWI was proposed by McFeeters [21] and uses satellite data to extract surface water bodies in wetland environments. The value of non-water bodies is zero or negative, while the value of water bodies is one or positive. $NDWI = Green - NIR / Green + NIR = B3 - B8 / B3 + B8$

- MNDWI

MNDWI was introduced by Xu [22] to improve the NDWI's accuracy in urban regions [35]. The near-infrared (NIR) band in NDWI has been replaced by the short-wave infrared (SWIR) band because SWIR shows the finer details of water properties [21] and is less susceptible to sediment concentration in water than NIR [36]. Water bodies in this case also have positive values, and non-water bodies have negative values.

$MNDWI = Green - SWIR1 / Green + SWIR1 = B3 - B11 / B3 + B11$

- MNDWI+5

MNDWI+VI was proposed by Menarguez [37] and used the near-infrared (NIR) and red bands to determine flood boundaries or survey water areas [20]. This index is effective for monitoring surface water resources [5]. In contrast to the indices employed in this study, the surface water will have negative values (<0).

$MNDWI+5 = NIR - Red / NIR + Red = B8 - B4 / B8 + B4$

- $AWEI_{sh}$

$AWEI_{sh}$ was first introduced by Feyisa, et al. [23], and it was developed to increase the accuracy of water extraction while maintaining a constant threshold value. This index is designed to enhance the detection of water bodies by removing shadow pixels. It uses a combination of blue, green, NIR, SWIR bands.

$AWEI_{sh} = Blue + 2.5 * Green - 1.5 * (NIR + SWIR1) - (0.25 * SWIR2) =$
$= B2 + 2.5 * B3 - 1.5 * (B8 - B11) - (0.25 * B12)$

After computing the above four water indices, the next step is to create a new band containing only water surfaces for each sentinel-2 acquisition by integrating all the information coming from these indices. For this purpose, the threshold value to classify the pixel as water is used. For the three water indices (NDWI, MNDWI, $AWEI_{sh}$), the threshold value is set to be greater than or equal to zero (>=0) to represent the water surface. However, for pixel values produced from the MNDWI+5 index, pixels with values below 0 (<=0) reflect the water surface. The resulting land-water masks are then merged to produce the final monthly land-water mask. Therefore, all four binary land-water masks are accumulated leading to values of zero for land (in all 4 indices) and one for water (in all 4 indices). The final processing step is to create the surface water area time series for all available months.

2.5.2. Classification of vegetation cover

In general, the topographical gradient strongly affects the flow of groundwater. [38]. The system's local flow is increasing with the topographic slope [25]. The vegetated areas are situated on the pathways of the groundwater: the line between regional water recharge and discharge into the lake (the direction of the topographic slope). Therefore, for Sawa lake, two directions were considered (West-Southwest of the lake) to estimate the vegetated areas, (Figure 3).

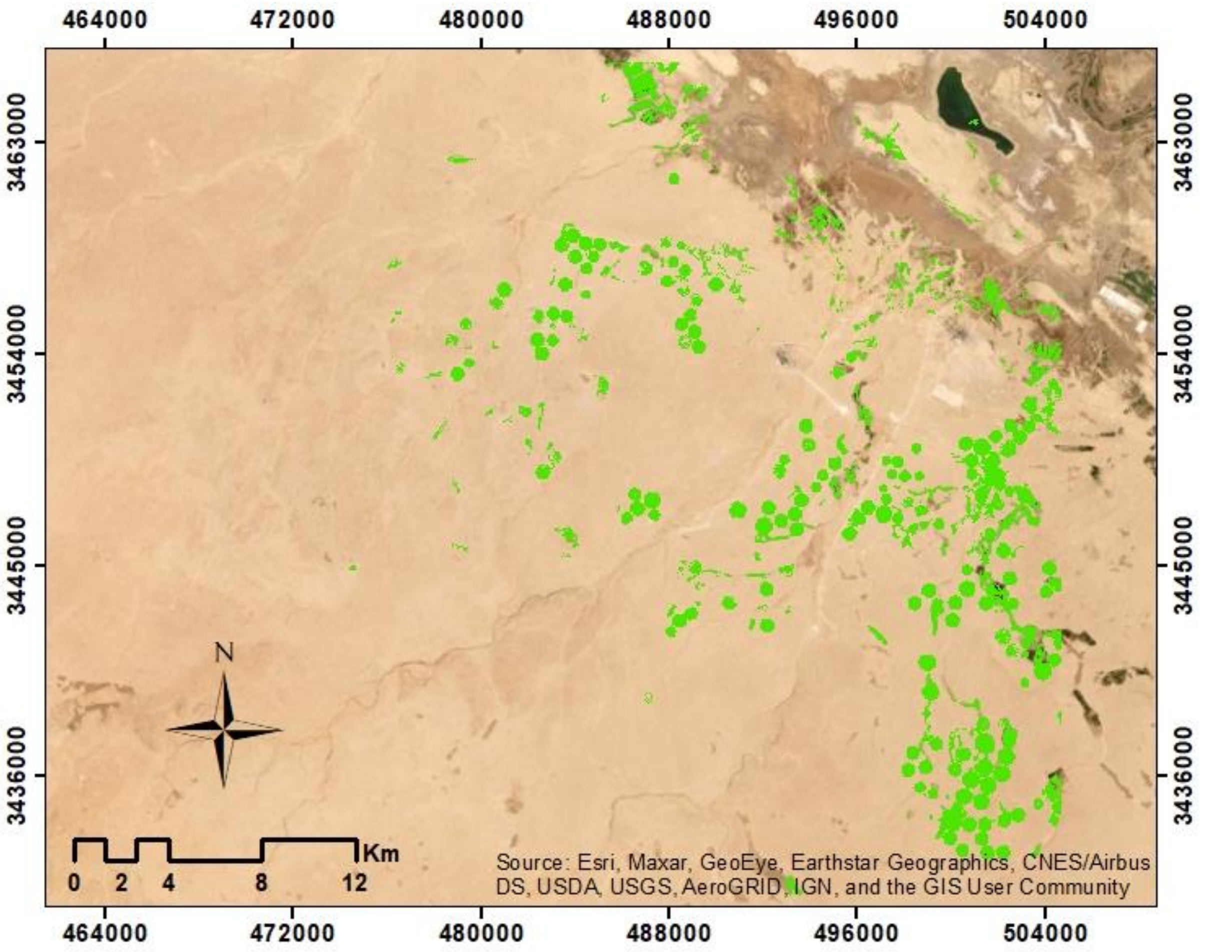

Figure 3. The boundary of the study area, that used to estimate the vegetation cover

The Normalized Difference Vegetation Index (NDVI) is one of the earliest vegetation indicators that was utilized to assess the severity of drought conditions [6, 39]. In this study, all Sentinel-2 images were processed to estimate the vegetated areas using NDVI.

Theoretically, NDVI values can range between -1 for non-vegetated surfaces to +1 for extensive vegetative cover. The NDVI values rise as the amount of green biomass grows, as positive seasonal changes occur, and as more favourable conditions exist (e.g., abundant precipitation) [40]. Based on NDVI values, vegetation density may be categorized into three groups. According to the USGS remote sensing phenology: The NDVI values of bare rock, sand, and snow are often relatively low (for example, 0.1 or less). Moderate NDVI levels may occur from low vegetation covers such as grasslands and shrubs, or senescing crops (between 0.2 to 0.5). High NDVI values (about 0.6 to 0.9) indicate an extensive vegetation cover, such as that seen in temperate and tropical forests or during the peak development stage of crops [40]. Based on NDVI values, a new band was created containing only the vegetated areas for each Sentinel-2 acquisition by masking the areas that have NDVI values >=0.3 for the study area.

2.6. Accuracy assessment

Thematic information generated from remote sensing data always contains some errors. Therefore, the acquired information should be assessed, and the degree of confidence should be determined before use by any end user or decision maker. To evaluate the accuracy of the derived maps, it is important to systematically compare two data sources, including categories that were classified by remote sensing data in a number of particular pixels and ground reference data collected at the same x, y position(ground control) [41]. A confusion matrix, also known as an error matrix, is frequently used to provide a summary of the relationship between these two data sources. Consequently, a number of different statistics, including overall accuracy (OA), and Kappa can be calculated [42].

OA is one of the most straightforward and widespread accuracy approaches [43]. It is calculated by dividing the number of correctly classified pixels (CCPs) by the number of total pixels. Individual class accuracy could also be determined using a similar method. For example, user accuracy can be obtained by dividing the total number of correct pixels in a category by the total number of pixels categorized in that category. In addition, the Kappa coefficient (K) is one of the widely used accuracy assessment methods. It evaluates inter-rater agreement for qualitative (categorical) items. However, compared to the straightforward percent computation, it is known as a more reliable approach. Because the procedure will take into consideration the possibility of the agreement that occurs by chance. This coefficient has a range of 1 (unreliable) to 1 (reliable) [44].

In this study, the accuracy of the maps of water bodies and vegetation cover derived from water and vegetation indices was evaluated using the Google Earth images archive [41, 43] since it was the only reliable resource available to utilize for this purpose. Only the Sentinel-2 images that had a time slice proportional to the high-resolution image archive on Google Earth were used for the evaluation of the indices. Consequently, the accuracy of the maps for the study area was assessed in three-time slices including Jun 2018, Aug 2019, and Jan 2021 for water and vegetation classes by a total of 600 ground control points (GCP) (200 points for each sentinel-2 image, including 70 points for lakes, 70 points for vegetation and the rest for bare lands).

3. Results and discussion

3.1. Accuracy of water body and vegetation cover mapping

After applying water and vegetation indices to the Sentinel-2 data time series from May 2016 and July 2022, the overall accuracy, and Kappa coefficient metrics were obtained using a confusion matrix for three selected maps. The overall accuracy for the maps of the months Jun 2018, Aug 2019, and Jan 2021 was more than 93%. Furthermore, the Kappa coefficient was 0.90, 0.92, and 0.89 for the three maps respectively (Table 3), which demonstrates that the work has been well verified.

Table 3. Accuracy assessment of the derived maps

Year	Classes	User Accuracy	Overall Accuracy	Kappa
Jun-18	Water	0.92	93%	0.90
	Vegetation	0.91		
Aug-19	Water	0.90	94%	0.92
	Vegetation	0.97		
Jan-21	Water	0.86	93%	0.89
	Vegetation	0.95		

3.2. Temporal analysis of surface water area

The surface water areas of Sawa lake are extracted from remotely sensed data, i.e., from the utilization of Sentinel-2 images. The surface water areas of Sawa lake are calculated and presented in Table 4. The table shows significant declining patterns in terms of the area of the lake of about 96% and 98% relative to the area of the lake derived from the initial image taken in May 2016.

Table 4. The estimated surface water area of Sawa Lake

Month	**Area-Km^2**	**Change %**	**Month**	**Area-Km^2**	**Change %**	**Month**	**Area-Km^2**	**Change %**
May-16	4.33		**Apr-18**	4.29	-1.11	**May-20**	4.08	-5.98
Jun-16	4.38	1.11	**May-18**	4.21	-2.86	**Jun-20**	3.73	-13.84
Jul-16	4.36	0.48	**Aug-18**	4.07	-6.21	**Jul-20**	3.51	-19.01
Sep-16	4.34	0.02	**Oct-18**	3.95	-8.88	**Aug-20**	3.62	-16.38
Nov-16	4.41	1.82	**Dec-18**	4.30	-0.76	**Sep-20**	3.59	-17.28
Dec-16	4.40	1.45	**Jan-19**	4.38	1.02	**Oct-20**	3.68	-15.04
Jan-17	4.40	1.55	**Mar-19**	4.47	3.09	**Jan-21**	4.52	4.27
Feb-17	4.38	0.95	**Apr-19**	4.32	-0.37	**May-21**	2.09	-51.75
Mar-17	4.35	0.46	**Jun-19**	4.13	-4.75	**Jul-21**	2.67	-38.44
Apr-17	4.38	0.99	**Jul-19**	4.16	-4.06	**Sep-21**	2.81	-35.09

Month	Area-Km^2	Change %	Month	Area-Km^2	Change %	Month	Area-Km^2	Change %
May-17	4.34	0.16	**Aug-19**	4.09	-5.68	**Oct-21**	2.95	-31.84
Jul-17	4.22	-2.54	**Sep-19**	4.03	-7.08	**Nov-21**	2.89	-33.29
Sep-17	4.20	-3.11	**Oct-19**	4.17	-3.81	**Feb-22**	3.44	-20.67
Oct-17	4.23	-2.49	**Nov-19**	4.20	-3.18	**Mar-22**	0.15	-96.45
Nov-17	4.23	-2.45	**Dec-19**	4.27	-1.38	**Apr-22**	0.25	-94.32
Dec-17	4.34	0.12	**Jan-20**	4.45	2.75	**May-22**	0.06	-98.62
Jan-18	4.51	4.01	**Feb-20**	4.58	5.58	**Jun-22**	0.50	-88.46
Mar-18	4.39	1.27	**Mar-20**	4.35	0.39	**Jul-22**	0.63	-85.46

The monthly estimate of the surface water area of the lake clearly displays the change in the surface of the lake over the past years. Consequently, there is a considerable decline in the area during the last six years between 2016-2022. For example, in May 2016 the calculated area is 4.33 Km^2 compared to 0.15 Km^2. In other words, the surface water area has decreased by about 4.2 Km^2, which indicates a serious drought that would result in a loss of 96% of the water's surface area by March 2022 compared to May 2016.

In addition to the area values in Table 4, Figure 4 presents the calculated surface water area as a graph time series in square kilometres with an additive trendline (Figure 4 a) and by comparing the seasonal changes of the surface water area of Sawa lake in spring and summer (Figure 4 b).

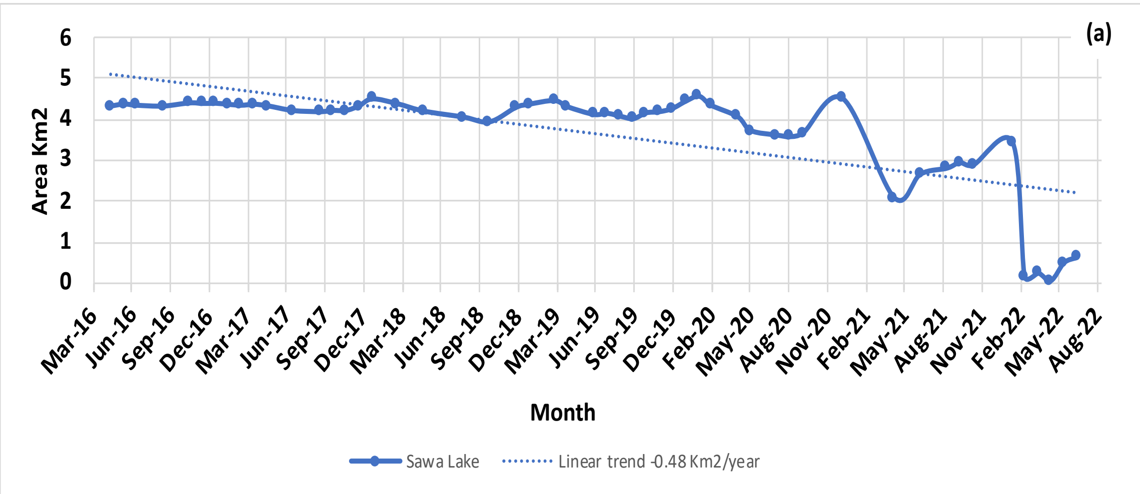

Figure 4a. The calculated surface water area of Sawa lake from May 2016 to July 2022 - monthly changes of surface water area of the lake. The linear trendline is presented in blue dots

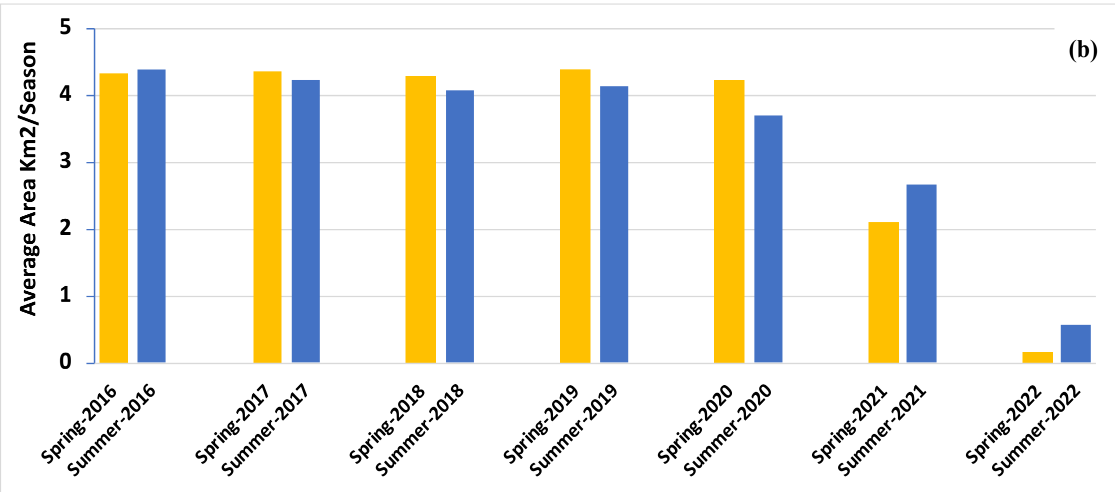

Figure 4b. The calculated surface water area of Sawa lake from May 2016 to July 2022. - comparing the seasonal changes of surface water area of Sawa lake in spring and summer seasons

The result exhibits seasonal behaviour. In general, the monthly time-series pattern fluctuates up during winter and spring and down during summer and autumn, however, this is not the case after 2020. Although the linear trend indicates that the extent of the surface water area is decreasing by -0.48 Km2/year, which is equivalent to approximately 11.25% per year, the most dramatic drop began in May 2021 (spring season) when the area of the lake loss of about 51% from its initial size in May 2016. By March 2022, the lake had disappeared and about 96% of the water's surface.

To facilitate the identification of changes in the surface water area of the lake, Figure 5 visualizes the spatial distribution of Sawa Lake that changed over several months. Figure 5a shows that between Jun-2016 and Jun-2019 there was a decrease in the surface water area of about 0.25 Km^2 with the most impacted regions being located in the north and south of the lake. However, the decline became more pronounced after 2019 in particular March-2022 the highest surface water area depression was unfortunately detected at more than 4.18 Km^2 relative to the first image in May 2016. This is a very serious indication of the drought trend and is also evident when considering Figures 4 a and b. After May 2022 (Figure 5b), the groundwater began to flow back into the lake through the supplied spring located in its centre of the lake in connection with the cessation of irrigation activities coming from wells in the surrounding area (see section 4.4 for more explanation).

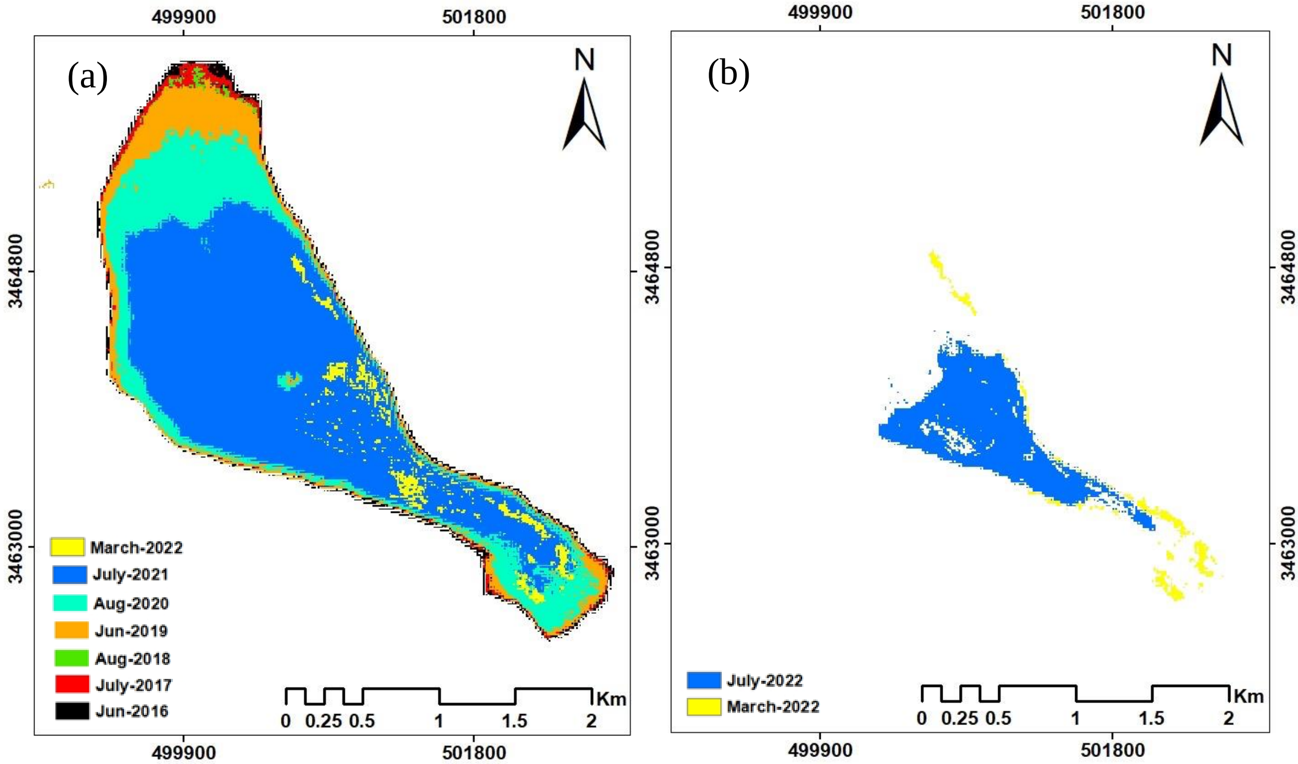

Figure 5. Spatial distribution of surface water area for a monitoring period of (a) Jun-2016 to March-2022, and (b) March-2022 to July-2022.

Overall, the results above completely match with the findings of the previous studies such as Mousa, et al. [25] and Awadh, et al. [26]. However, these studies referred only to the annual changes in Sawa lake, and they did not discuss the monthly behaviour of the lake.

3.3. Impact of Precipitation on the change of Surface Water of the Lake

Rainfall represents one of the key elements influencing the change in the surface water body [45]. Therefore, the relationship between the water surface of Sawa lake and rainfall data was examined. A seasonal trend can be seen in the data presented in Figure 6, which shows that the majority of precipitation occurs during the winter and spring seasons. However, in some years, such as 2018, the precipitation began in the autumn season. From 2016 through 2022, the average monthly rainfall during the rainy season is 17 mm/month. Significant rainfall events in 2018 and 2021 contributed to the above estimation. However, this is a small value in comparison to the significant loss in lake surface area over the same period. In addition, the results of the statistical test analysis between the detrending time series of Sawa lake (to focus on the fluctuation) (Figure 7) and rainfall data show that there was no difference at a 95% level of confidence (t stat= -1.20, p=0.23). Therefore, it is evident that the lack of rainfall is not the direct cause of the drought of Sawa lake.

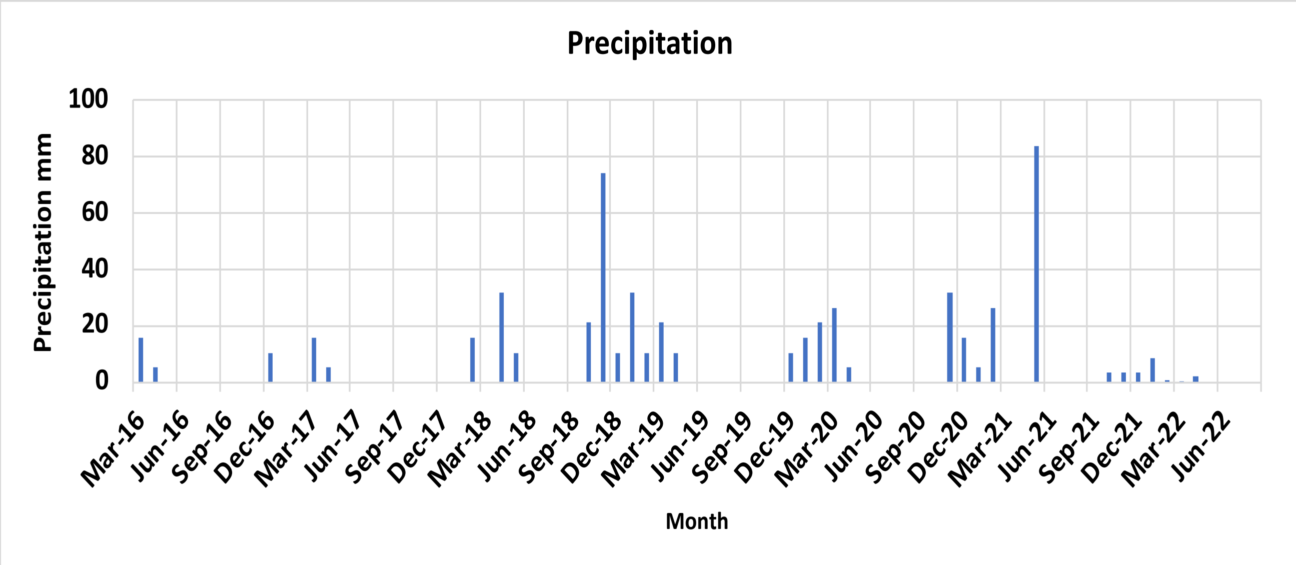

Figure 6. The monthly rainfall data in mm for the study area. Data source is https://power.larc.nasa.gov/data-access-viewer / accessed on 16 June 2022)

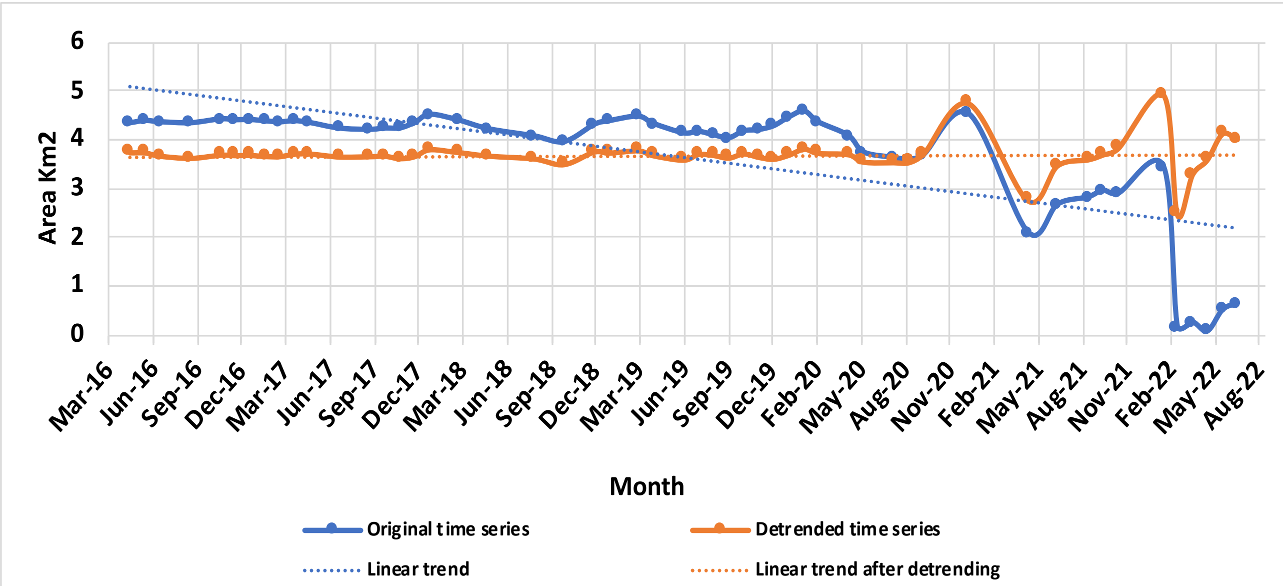

Figure 7. The original time-series of Sawa lake before and after detrending

3.4. Impact of human activities on the change of surface water of the lake

The second factor influencing the dynamics of open surface water is human activities. In this study, the vegetation cover based on NDVI and Al-Samawah saltpan lake were used as a measure of human activities factors.

The vegetation cover in the study region (Figure 3) consists primarily of circular farms (Center pivot irrigation) planted with major strategic crops, namely wheat and barley. These farms are irrigated mainly by groundwater because the land is situated above the Euphrates River. Figure 8 depicts the increase in vegetation cover between 2016 and 2022. The vegetation cover is shown for selected months of the growing season, except for the last image (July 2022), to illustrate the effect of agricultural activities on the drought of Sawa lake. A visual inspection of the figure reveals a clear upward trend in agricultural lands.

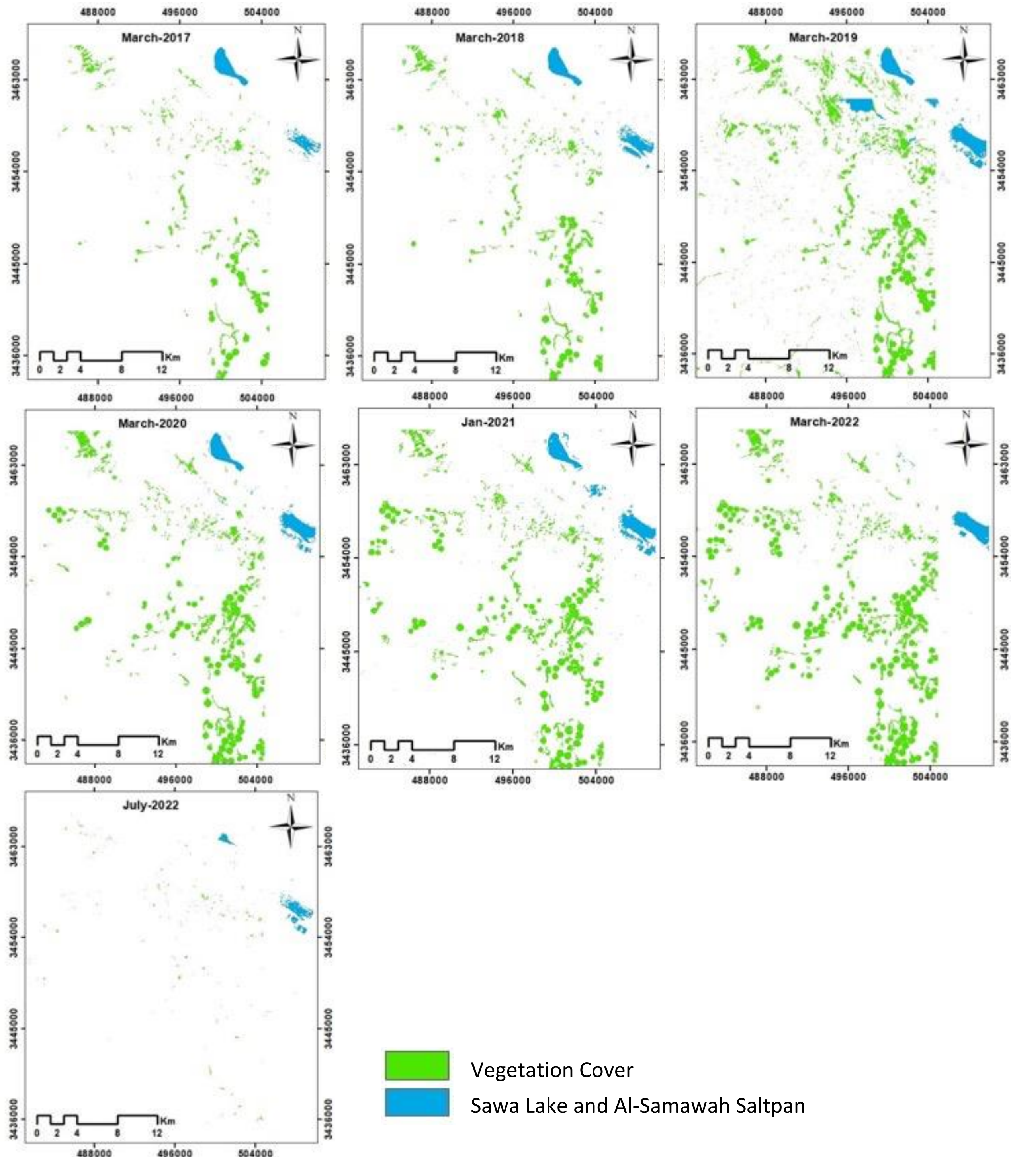

Figure 8. The estimated vegetation cover based on NDVI for the period 2016-2022 for selected month for the lands near Sawa lake. The vegetation cover is represented by green color, while the blue color refers to Sawa lake and Al-Samawa Saltpan.

To determine the growth in agricultural lands, the monthly time series of vegetation cover is estimated and presented in Figure 9. The data demonstrate a seasonal trend with substantial vegetation cover throughout winter and spring (growing seasons). The linear trend suggests that the amount of vegetation cover (agricultural lands) is increasing by 3.15 Km^2/year, which is equivalent to approximately 15.43% each year. Comparing the peak of agriculture activities between two consecutive years reveals that the vegetation cover grew by 37%, from 20.4 km^2 in March 2017 to 28 km^2 in March 2018. Similarly, the vegetation cover increased by 16 km^2 in March 2022 compared to January 2021 (+29%). The dramatic rise in vegetation cover over the winter of 2018 and spring of 2019 can be interpreted as a plant invasion following a flood event [46] in Iraq that affected the NDVI results. The agricultural lands in the study area have increased by 254% during the study period (from March 2017 to April 2022). In general, increasing agricultural lands mean increasing water demand for irrigation and reducing the annual flow into the lake [47].

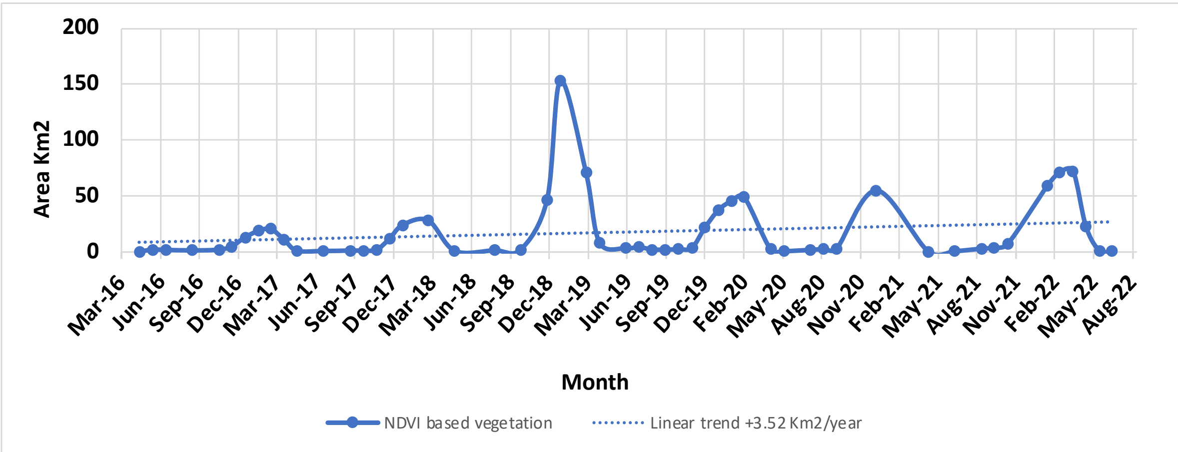

Figure 9. The monthly time-series of vegetation area near Sawa Lake for the period May 2016-July 2022 with the linear trendline in blue dots.

For Al-Samawah saltpan lake, the monthly estimation of surface water area is presented in Figure 10. The result displays a significant seasonal behaviour. The monthly time-series pattern, in general, demonstrates the transition from dry summers beginning as early as June to winter. Accordingly, there is a slight increase in surface water area before 2019, however, it increases significantly from 2019 to 2022. The linear trend of Al-Samawah saltpan lake shows an upward trend of around +0.45 km2/year, which is equal to an annual increase of 20% (relative to the surface water area derived from the first image (May 2016)).

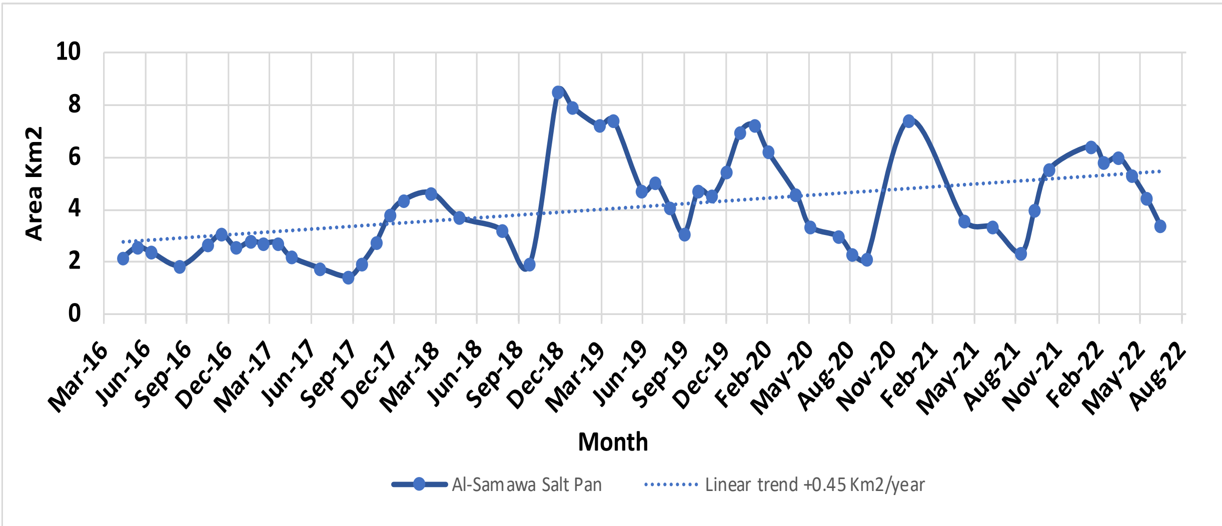

Figure 10. The monthly variation of surface water body of Al-Samawa Saltpan for the period May 2016-July 2022 with the linear trendline in blue dots.

In general, the results presented in Figure 8 indicate that between March 2017 and March 2019 there was an increase in both vegetation cover and the surface water area of Samawah saltpan lake, but this had no effect on the surface water area of Sawa lake. However, following 2019, the lake's surface water area began to decrease until it disappeared in March 2022 which can be interpreted as a result of the continuous growth in the vegetation cover, the increase in the surface water area of the saltpan lake and the lack of water supply in the study region. The gradual increase in the surface water area of Sawa Lake after March 2022 in particular July 2022 showed that lake recovery is possible. During this time, there are no agricultural activities taking place inside the Sawa region; nevertheless, pumping water to the Samawah saltpan lake continues almost throughout the year to extract the salt.

A number of different hypotheses have been proposed as potential explanations for the reduction in the size of Sawa lake. Some have suggested that the major river that fed the lake was destroyed as a result of shifting tectonic plates caused by earthquakes. Others believe that climate change, especially reduced rainfall, and increased evaporation had a role in the destruction. In this regard, the relationship between the drought of Sawa lake and human activities which is represented by increasing in vegetation cover and salt production has been identified as a cause and will be further investigated by statistical test analysis.

After detrending the time-series of Sawa lake, the vegetation cover and Al-Samawah saltpan lake to remove the seasonal pattern and focus on the fluctuation, the statistical test analysis has been applied. The results show that the difference between the surface water area of Sawa lake and the estimated area of vegetation was significant at the 95% level of confidence (t stat = -6.07 and p =0.00). In addition, the results reveal that the calculated surface water areas for both Sawa lake and Al-Samawah saltpan lake were significant difference at a 95% confidence level (t stat = -2.05 and p =0.04).

These results indicate that the overexploitation of groundwater has had a considerable impact on the flow of groundwater into Sawa lake, which is its source of water. The results of this study support the hypothesis that the expansion of wells in the area close to the lake disrupted the subsurface recharge channels of the spring that supply the lake with water. Consequently, it is vital to educate the local people on the significance of water and develop a sustainable system for the management of water resources. This can be achieved by continuous monitoring of illegal practices caused by human activities that affect the groundwater, training in water conservation techniques, water management, improvement of agricultural methods, and the cultivation of low-water-use crops that all contribute to the lake's rehabilitation.

4. Conclusion

In this study, Sentinel-2 images were used to monitor the monthly fluctuations of the surface water area of Sawa lake between May 2016 and July 2022.

Mismanagement of water and human activities (agricultural and industrial policies) along with the water shortage have had negative impacts on the Sawa lake ecosystem resulting in the drying up of the lake. The results of this study indicated that the surface water area of Sawa lake shrank from 4.33 km2 in May 2016 to 0.15 km2 in March 2022. That is, 96% of the surface water area of the lake dried up during the period from May 2016 until March 2022. On the other hand, the maximum area of agricultural land was estimated at 72.16 km^2 in 2022, indicating an increase of 254% compared to its maximum area (20.41 km^2 in 2017). In addition, the surface water area of Al-Samawah saltpan lake increased by approximately 121% for the same period. This inverse relationship between the shrinking of Sawa lake and the increasing of both agricultural lands and the surface water area of the Al-Samawah saltpan is concerning. The findings of the water and vegetation indices for July 2022 suggested that the water of the lake would be able to be restored in the absence of human activities.

These results suggest that the rapid transformation of landscapes into agricultural lands at the expense of dominant ecosystems like pastures and other vegetation, as well as the rising groundwater depletion that is the only source of irrigation, pose a great risk of losing the dominant environment of the lake. Accordingly, human activities represent the direct cause of the drought that has affected Sawa lake. The results of statistical test analysis show that the difference between the surface water area of Sawa lake and the estimated area of both vegetation cover and Al-Samawah Saltpan artificial lake was significant at a 95% level of confidence. These results can be used by decision-makers and responsible administrators to better understand the area, number and factors affecting changes in the surface water. This allows for the development of reasonable plans in the areas of water resource management, irrigation of crops, and environmental conservation, to promote sustainable water usage.

Declaration of Competing Interest

The authors declare that they have no recognized non-financial or financial competing interests in any materials conversed in the current work.

Funding
No funding was gained from any financial organization for conducting the current work.

References

[1] J.-H. Ryu, K.-S. Han, Y.-W. Lee, N.-W. Park, S. Hong, C.-Y. Chung, *et al.*, "Different Agricultural Responses to Extreme Drought Events in Neighboring Counties of South and North Korea," *Remote Sensing,* vol. 11, 2019.
[2] Y. Kang, S. Khan, and X. Ma, "Climate change impacts on crop yield, crop water productivity and food security – A review," *Progress in Natural Science,* vol. 19, pp. 1665-1674, 2009.
[3] N. R. Bond, P. S. Lake, and A. H. Arthington, "The impacts of drought on freshwater ecosystems: an Australian perspective," *Hydrobiologia,* vol. 600, pp. 3-16, 2008.
[4] A. Dai, "Drought under global warming: a review," *WIREs Climate Change,* vol. 2, pp. 45-65, 2010.
[5] T. D. Bhaga, T. Dube, M. D. Shekede, and C. Shoko, "Impacts of Climate Variability and Drought on Surface Water Resources in Sub-Saharan Africa Using Remote Sensing: A Review," *Remote Sensing,* vol. 12, 2020.
[6] H. A. A. Gaznayee, A. M. F. Al-Quraishi, K. Mahdi, and C. Ritsema, "A Geospatial Approach for Analysis of Drought Impacts on Vegetation Cover and Land Surface Temperature in the Kurdistan Region of Iraq," *Water,* vol. 14, 2022.
[7] A. F. Van Loon, T. Gleeson, J. Clark, A. I. J. M. Van Dijk, K. Stahl, J. Hannaford, *et al.*, "Drought in the Anthropocene," *Nature Geoscience,* vol. 9, pp. 89-91, 2016.
[8] A. Schucknecht, S. Erasmi, I. Niemeyer, and J. Matschullat, "Assessing vegetation variability and trends in north-eastern Brazil using AVHRR and MODIS NDVI time series," *European Journal of Remote Sensing,* vol. 46, pp. 40-59, 2017.
[9] A. M. Fadhil, "Drought mapping using Geoinformation technology for some sites in the Iraqi Kurdistan region," *International Journal of Digital Earth,* vol. 4, pp. 239-257, 2011.
[10] IdRC, "Capacity Assessment for Drought Risk Management in Iraq; Final Report," Amman, Jordan2012.
[11] R. Harun, I. Muresan, F. Arion, D. Dumitras, and R. Lile, "Analysis of Factors that Influence the Willingness to Pay for Irrigation Water in the Kurdistan Regional Government, Iraq," *Sustainability,* vol. 7, pp. 9574-9586, 2015.
[12] J. Helali, S. Asaadi, T. Jafarie, M. Habibi, S. Salimi, S. E. Momenpour, *et al.*, "Drought monitoring and its effects on vegetation and water extent changes using remote sensing data in Urmia Lake watershed, Iran," *Journal of Water and Climate Change,* vol. 13, pp. 2107-2128, 2022.
[13] V. Diaz, G. A. Corzo Perez, H. A. J. Van Lanen, D. Solomatine, and E. A. Varouchakis, "An approach to characterise spatio-temporal drought dynamics," *Advances in Water Resources,* vol. 137, 2020.
[14] R. Benedetti, P. Rossini, and R. Taddei, "Vegetation classification in the Middle Mediterranean area by satellite data," *International Journal of Remote Sensing,* vol. 15, pp. 583-596, 2007.
[15] X. Huang, C. Xie, X. Fang, and L. Zhang, "Combining Pixel- and Object-Based Machine Learning for Identification of Water-Body Types From Urban High-Resolution Remote-Sensing Imagery," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 8, pp. 2097-2110, 2015.
[16] M. Ford, "Shoreline changes interpreted from multi-temporal aerial photographs and high resolution satellite images: Wotje Atoll, Marshall Islands," *Remote Sensing of Environment,* vol. 135, pp. 130-140, 2013.
[17] X. Yang, Q. Qin, H. Yésou, T. Ledauphin, M. Koehl, P. Grussenmeyer, *et al.*, "Monthly estimation of the surface water extent in France at a 10-m resolution using Sentinel-2 data," *Remote Sensing of Environment,* vol. 244, 2020.
[18] W. Li and P. Gong, "Continuous monitoring of coastline dynamics in western Florida with a 30-year time series of Landsat imagery," *Remote Sensing of Environment,* vol. 179, pp. 196-209, 2016.
[19] S. Xulu, K. Peerbhay, M. Gebreslasie, and R. Ismail, "Drought Influence on Forest Plantations in Zululand, South Africa, Using MODIS Time Series and Climate Data," *Forests,* vol. 9, 2018.
[20] Y. Zhou, J. Dong, X. Xiao, T. Xiao, Z. Yang, G. Zhao, *et al.*, "Open Surface Water Mapping Algorithms: A Comparison of Water-Related Spectral Indices and Sensors," *Water,* vol. 9, 2017.

[21] S. K. McFeeters, "The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features," *International Journal of Remote Sensing,* vol. 17, pp. 1425-1432, 2007.
[22] H. Xu, "Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery," *International Journal of Remote Sensing,* vol. 27, pp. 3025-3033, 2007.
[23] G. L. Feyisa, H. Meilby, R. Fensholt, and S. R. Proud, "Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery," *Remote Sensing of Environment,* vol. 140, pp. 23-35, 2014.
[24] B. Chisadza, M. J. Tumbare, W. R. Nyabeze, and I. Nhapi, "Linkages between local knowledge drought forecasting indicators and scientific drought forecasting parameters in the Limpopo River Basin in Southern Africa," *International Journal of Disaster Risk Reduction,* vol. 12, pp. 226-233, 2015.
[25] Y. A. Mousa, A. F. Hasan, and P. Helmholz, "Spatio-Temporal Analysis of Sawa Lake’s Physical Parameters between (1985–2020) and Drought Investigations Using Landsat Imageries," *Remote Sensing,* vol. 14, 2022.
[26] S. M. Awadh, A. H. Al-Sulttani, and Z. M. Yaseen, "Temporal dynamic drought interpretation of Sawa Lake: case study located at the Southern Iraqi region," *Natural Hazards,* vol. 112, pp. 619-638, 2022.
[27] A. M. R. Al-Taee, E. A. Al-Emara, and A. A. Maki, "The Bacterial Fact of Sawa Lake in Samawa City Southern Iraq," *Syrian Journal of Agrcultural Research SJAR,* vol. 5, pp. 321-328, 2018.
[28] S. Awadh, "Outstanding Universal Values of the Sawa Lake as A World Natural Heritage," *Bull. Iraq nat. Hist. Mus.,* vol. 14, pp. 1-11, 2016.
[29] W. Al-Mosawi, M. Al-Tememi, H. Ghalib, and N. Nassar, "Sub-Bottom Profiler and Side Scan Sonar investigations, with the assistance of hydrochemical and isotopic analysis of Sawa Lake, Al-Muthana Governorate, Southern Iraq.," *Mesop. J. Mar. Sci.,* vol. 30, pp. 81-97, 2015.
[30] M. K. Al-Tememi, W. M. Al-Mosawi, and Z. A. Abdulnabi, "Monitoring the Change of Water Level and Its Effect on Water Quality in Sawa Lake, Southwest Iraq," *Iraqi Journal of Science,* pp. 2177-2185, 2019.
[31] C. Schwatke, D. Scherer, and D. Dettmering, "Automated Extraction of Consistent Time-Variable Water Surfaces of Lakes and Reservoirs Based on Landsat and Sentinel-2," *Remote Sensing,* vol. 11, 2019.
[32] M. Drusch, U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, *et al.*, "Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services," *Remote Sensing of Environment,* vol. 120, pp. 25-36, 2012.
[33] ESA, "Sen2Cor—Configuration and User Manual," Paris, France, Technical Report2018.
[34] Serco Italia SPA, "Drought monitoring with Sentinel-2 - Western Cape Province, 2015-2020," Retrieved from RUS Lectures2021.
[35] C. Huang, Y. Chen, S. Zhang, and J. Wu, "Detecting, Extracting, and Monitoring Surface Water From Space Using Optical Sensors: A Review," *Reviews of Geophysics,* vol. 56, pp. 333-360, 2018.
[36] G. Sarp and M. Ozcelik, "Water body extraction and change detection using time series: A case study of Lake Burdur, Turkey," *Journal of Taibah University for Science,* vol. 11, pp. 381-391, 2018.
[37] M. A. Menarguez, "Global Water Body Mapping from 1984 to 2015 Using Global High Resolution Multispectral Satellite Imagery," *University of Oklahoma: Norman, OK, USA,* 2015.
[38] L. E. Condon and R. M. Maxwell, "Evaluating the relationship between topography and groundwater using outputs from a continental-scale integrated hydrology model," *Water Resources Research,* vol. 51, pp. 6602-6621, 2015.
[39] Y. Yao, Q. Qin, A. M. Fadhil, Y. Li, S. Zhao, S. Liu, *et al.*, "Evaluation of EDI derived from the exponential evapotranspiration model for monitoring China’s surface drought," *Environmental Earth Sciences,* vol. 63, pp. 425-436, 2011.
[40] D. d. N. Aquino, O. C. d. Rocha Neto, M. A. Moreira, A. d. S. Teixeira, and E. M. d. Andrade, "Use of remote sensing to identify areas at risk of degradation in the semi-arid region," *Revista CiÊncia AgronÔmica,* vol. 49, 2018.
[41] A. Darvishi Boloorani, R. Papi, M. Soleimani, L. Karami, F. Amiri, and N. Neysani Samany, "Water bodies changes in Tigris and Euphrates basin has impacted dust storms phenomena," *Aeolian Research,* vol. 50, 2021.
[42] R. G. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sensing of Environment,* vol. 37, pp. 35-46, 1991.

[43] V. H. Nhu, A. Mohammadi, H. Shahabi, A. Shirzadi, N. Al-Ansari, B. B. Ahmad, *et al.*, "Monitoring and Assessment of Water Level Fluctuations of the Lake Urmia and Its Environmental Consequences Using Multitemporal Landsat 7 ETM(+) Images," *Int J Environ Res Public Health,* vol. 17, Jun 12 2020.

[44] R. G. Pontius and M. Millones, "Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment," *International Journal of Remote Sensing,* vol. 32, pp. 4407-4429, 2011.

[45] W. Yigzaw and F. Hossain, "Water sustainability of large cities in the United States from the perspectives of population increase, anthropogenic activities, and climate change," *Earth's Future,* vol. 4, pp. 603-617, 2016.

[46] T. Kiss, J. Nagy, I. Fehervary, and C. Vaszko, "(Mis) management of floodplain vegetation: The effect of invasive species on vegetation roughness and flood levels," *Sci Total Environ,* vol. 686, pp. 931-945, Oct 10 2019.

[47] Y. Alizade Govarchin Ghale, M. Baykara, and A. Unal, "Investigating the interaction between agricultural lands and Urmia Lake ecosystem using remote sensing techniques and hydro-climatic data analysis," *Agricultural Water Management,* vol. 221, pp. 566-579, 2019.