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Impacts of droughts and human activities on water quantity and quality: Remote sensing observations of Lake Qadisiyah, Iraq

Dalin Jiang [a,*], Ian Jones [a], Xiaohan Liu [b], Stefan G.H. Simis [b], Jean-François Cretaux [c], Clement Albergel [d], Andrew Tyler [a], Evangelos Spyrakos [a]

[a] *Earth and Planetary Observation Sciences (EPOS), Biological and Environmental Sciences, Faculty of Natural Sciences, University of Stirling, Stirling FK9 4LA, United Kingdom*
[b] *Plymouth Marine Laboratory, Plymouth PL1 3DH, United Kingdom*
[c] *LEGOS, Université de Toulouse, CNES, CNRS, IRD, UPS, 31400, Toulouse, France*
[d] *European Space Agency Climate Office, ECSAT, Harwell Campus, Didcot, Oxfordshire, United Kingdom*

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ABSTRACT

Water quantity and quality in lakes are closely linked to the compounding effects of climate change and human activities in their catchments, especially for lakes located in semi-arid and arid regions where water resources are scarce. Whilst knowledge gaps exist for these effects in semi-arid and arid region lakes due mainly to the lack of long-term *in situ* monitoring data. By using satellite remote sensing data, this study firstly investigated the variations of water level, chlorophyll-*a* concentration (Chl-*a*) and turbidity in Lake Qadisiyah, Iraq between 2000 and 2019. Results showed that the average water level was 138.3 m in 2000–2019, it decreased clearly in 2001, 2009, 2015 and 2018 with the lowest value of 120 m in July 2015. The mean Chl-*a* was 6.3 mg/m^3 and it showed an overall increasing trend during 2000 and 2019. Turbidity showed extremely high values (>10 NTU) in 2009 and 2017–2018 compared to the mean value of 3.6 NTU in 2000–2019. The boosted regression tree (BRT) was then used to explore the relationship between those variations and El Niño-Southern Oscillation, droughts, meteorological factors and land use land cover changes in the catchment. Results revealed that water level declines were mainly associated with droughts led by La Niña events. Chl-*a* increase in the lake were mainly explained by built-up area increase and water area decrease in the catchment, with a relative contribution of 29.2 % and 28.6 % respectively. Water area changes in the catchment were the main factor influencing turbidity explaining 55.3 % of the variation. An exception water level decline in 2014–2016 was also observed when there was no drought, which was most likely caused by the cut off of water flow upstream and the release of water from the dam during periods of war. The findings in this study underscored the impacts of climate and human activities on water quantity and quality in semi-arid region lakes. Actions such as improving water use efficiency, establishing water storages, and enhancing cross-border cooperation are therefore recommended to deal with extreme events. Pollution control measures in the catchment are also suggested to prevent water quality deterioration in the lake.

1. Introduction

Lakes play an important role in ecosystem services such as agriculture, fisheries, supply of drinking water, tourism and recreation, production of hydroelectricity, and others (Schallenberg et al., 2013; Reynaud and Lanzanova, 2017; Sterner et al., 2020). However, many lakes in the world are experiencing pressures from climate change and/or anthropogenic drivers, which threaten the ecosystem services they provide (Woolway et al., 2020). It is projected that the global population will continue growing and reach a peak of around 10.4 billion in 2080s (UN, 2022). Global warming will continue until at least mid-century resulting in more frequent and intense regional extremes such as heatwaves, heavy precipitation and droughts (IPCC, 2021). These factors will threaten further water resource availability and lake ecosystem health.

Several studies have shown evidence of climate variability and other anthropogenic impacts on lakes, which consequently led to changes in water quantity and quality, and altered their ecological functions and

* Corresponding author.
E-mail address: dalin.jiang@stir.ac.uk (D. Jiang).

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status (Tao et al., 2015; Chen et al., 2022; Bai et al., 2024). For example, the number of lakes and lake water surface area in the Mongolia Plateau have decreased dramatically since the 1970s, which were mainly because of combined impact of decreasing precipitation and prevalence of coal mining activities in the region (Tao et al., 2015). Yao et al. (2023) reported that 53 % of the global lakes have significant decline in storage, which was largely because of climate change and human activities, and the drying of lakes was estimated to have impacts on about one-quarter of the world's population.

Variations in precipitation and evaporation are tightly linked with water balance in the catchment, which influences the water quantity in the lake, and can lead to changes in water quality in the lake (Adrian et al., 2009; Bai et al., 2011; Seitz et al., 2022; Zhao et al., 2022). As a result, lakes in arid or semi-arid climate zones are particularly sensitive to climate changes, and it was estimated that water losses have happened to 60 % of water bodies in arid regions (Yao et al., 2023). Lake Qadisiyah, which is located on the Euphrates River in the north of Iraq in a semi-arid region with low precipitation levels, provides important water resources for irrigation, and is the second largest hydropower dam in Iraq (Al-Kayiem and Mohammad, 2019; Tayyeh and Mohammed, 2024). It is reported that the Euphrates River flow decreased to approximately 30 % of its normal flow when it crossed into Iraq because of droughts during 2007 and 2009, and led to a dramatic water area decline of 72 % in Lake Qadisiyah (Chulov, 2009; Hasan et al., 2019). The droughts caused severe health issues and water shortages for drinking, electricity generation and irrigation, and approximately 1000 new groundwater wells were dug from 2007 to 2009 in response to water shortage (Chulov, 2009). In addition to climate, water in Lake Qadisiyah can be affected by dams in upstream countries because of the cross-boundary Euphrates River (Chulov, 2009), and waters in this lake and its connected rivers were sometimes weaponised during military conflicts (UNEP, 2017), which added further disturbance to this lake. Those facts emphasize the importance of studying the variations of water quantity, quality and their relationship in Lake Qadisiyah, and this lake being a good study area for exploring how climate and human activities impact water ecosystem, to support sustainable use of water resources and deal with water shortages caused by extreme events in the future.

Although some studies have reported decreasing water level in Lake Qadisiyah (e.g., Gao et al., 2012; Voss et al., 2013; Titolo, 2021), knowledge gaps still exist regarding to detailed lake water level changes with associated water quality changes in the past twenty years, and how those changes were linked to climate change and human activities. As in many lake systems, one of the barriers for carrying out those studies is the scarcity of long-term monitoring data with a good consistency. Earth observation provides an efficient way to monitor water quantity variables, such as water level, water extent and water volume (Pekel et al., 2016; Cretaux et al., 2018; Carrea et al., 2023; Li et al., 2023), and water quality variables, such as Chlorophyll-*a* concentration (Chl-*a*), turbidity and water transparency (Neil et al., 2019; Dogliotti et al., 2015; Jiang et al., 2019; Liu et al., 2021) in inland waters. Satellite data archives can be used to monitor long-term variations of water quantity and quality, providing valuable data for regions where *in situ* data are lacking (Setiawan et al., 2019; Cao et al., 2022; Carrea et al., 2023).

This study exploits the use of Earth observation data to: (1) investigate the variations of water level, water quality variables (Chl-*a* and turbidity), and the potential relationships between water level fluctuations and water quality changes over the last twenty years in Lake Qadisiyah; (2) examine the main drivers of these changes considering climate and human activities.

2. Methodology

2.1. Study area

Lake Qadisiyah is located on the Euphrates River in the north of Iraq (Fig. 1a). It was created after the construction of the Hadithah dam in 1977 (red point in Fig. 1b), with the purpose of regulating runoff from the Euphrates River, providing irrigation for local fields, producing hydroelectricity, and partially controlling floods (Kamnev et al., 1983). The Hadithah dam is the second largest dam in Iraq and regulates the Euphrates River for the whole country (UNEP, 2017). The designed normal water level of the dam is 143 m with a storage of 6.4 km^3 (Kamnev et al., 1983) and the surface area of the lake is 428 km^2 (derived from the Landsat-8 image on 2020-08-28). Its catchment is approximately 294,025 km^2, covering parts of Turkey, Syria and Iraq (Fig. 1a), and the majority land cover type is bare land. Because of the elevation of the catchment, the semi-arid climate of this region, and the adjacent Mediterranean to the north, there is higher precipitation in the northern mountain areas of the catchment compared to the southern

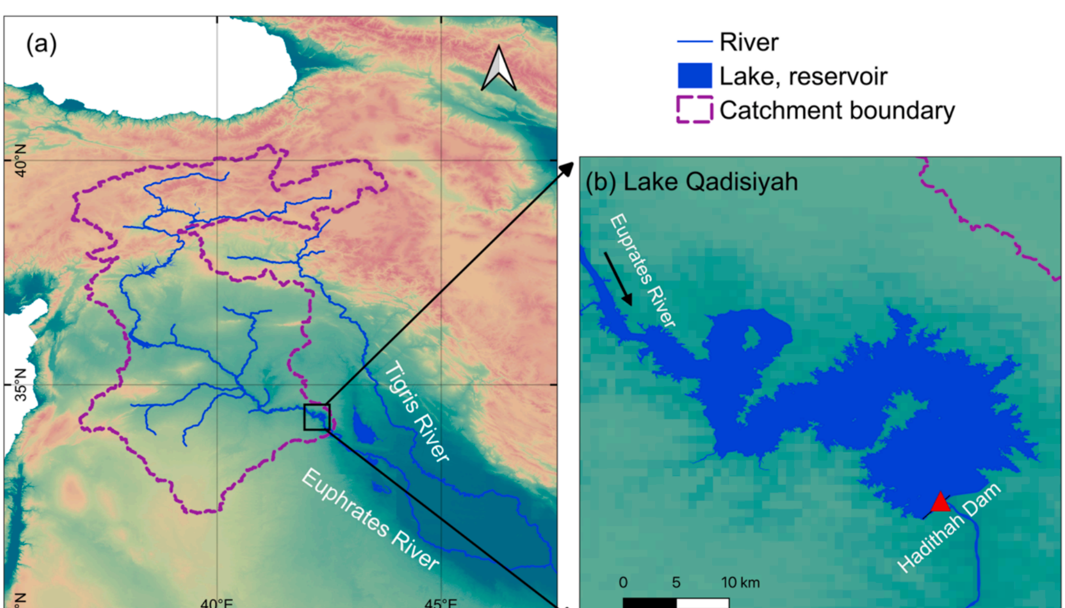

Fig. 1. Study area, (a) the catchment of Lake Qadisiyah, and (b) Lake Qadisiyah in Iraq. Background colour indicates the elevation, with red and teal meaning high and low values respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

plains in the catchment (Daggupati et al., 2017; Kool et al., 2020). Inflow water is mainly from snowmelt and rainfalls in the catchment from November to May (Kamnev et al., 1983), and Euphrates is the main river bringing waters to the west of the lake after flowing through several dams in upstream (Fig. 1b). The average Chl-*a* and turbidity in this lake are 6.3 mg/m^3 and 3.6 NTU, according to the satellite products used in this study.

2.2. Data collection and processing

Daily water level, Chl-*a*, turbidity and water-leaving reflectance (R_w) data between 2000 and 2019 for Lake Qadisiyah were obtained from the European Space Agency (ESA) Climate Change Initiative Lake (Lakes_cci) version 1.0 dataset (https://climate.esa.int/en/projects/lakes/data/). In the Lakes_cci dataset, water level was derived from radar altimetry data from sensors onboard TOPEX/Poseidon, ERS-2, Envisat, Cryosat-2 and Saral, and provided as a single lake-wide estimate. R_w data were acquired from the Medium Resolution Imaging Spectrometer (MERIS, 2002–2012) and Sentinel-3 Ocean and Land Colour Instrument (OLCI, 2016–2019) with a spatial resolution of 1 km after atmospheric correction using Polymer (Steinmetz et al., 2011). Cloud and cloud shadows were identified and masked using the Idepix in Sentinel Application Platform (SNAP). Chl-*a* and turbidity were estimated from R_w using a blended algorithm based on optical water type (OWT) classification, algorithm details are provided in Simis et al. (2020) and Liu et al. (2021). The downloaded Chl-*a* and turbidity data from Lakes_cci dataset include pixels with potential influence from land, so two more steps in addition to the Lakes_cci processing procedure were carried out in this study. First, the normalised difference water index (NDWI, Xu, 2006) was calculated from R_w for each image, and a threshold of NDWI < 0.1 was applied to exclude pixels with influence from land or shallow water. Second, pixels affected by nearby land ("adjacency affect") were detected and masked out using an OWT approach from Jiang et al. (2023). In addition, images where the number of valid pixels covers less than half of the lake (<50 %) were excluded to avoid any representativity issues, which was typically due to cloud cover. The remaining images were considered to be of good quality and representative of the lake system.

Meteorological, climate and land use land cover data in the lake catchment were used in this study to determine the factors influencing water quantity and quality changes in Lake Qadisiyah. Lake catchment was determined using the GTOPO30 digital elevation model (DEM) data downloaded from USGS (https://earthexplorer.usgs.gov). Meteorological data including monthly air temperature (at 2 m height), total precipitation and wind speed data in the lake catchment were sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis V5 (ERA5) dataset with a spatial resolution of 0.25 degree. Climate data including standardised precipitation index (SPI) in the lake catchment with a spatial resolution of 0.25 degree and Multivariate El Niño/Southern Oscillation (ENSO) index (MEI) with a single value globally from 2000 to 2019 were downloaded from the Copernicus Emergency Management Service (EMS, https://emergency.copernicus.eu) and the National Oceanic and Atmospheric Administration (NOAA, https://psl.noaa.gov/enso/mei/). An SPI smaller than −1.0 means drier than normal, and lower SPI indicates severe drought (EMS). A MEI value higher than 0.5 and lower than −0.5 indicates warm and cold periods, respectively (NOAA). Land use land cover (LULC) types in the lake catchment were determined from the MODIS MCD12Q1 product with a spatial resolution of 500 m, which includes types of forest, shrubs and grassland, cropland, built-up, bare land, and water bodies. The percentage of area of each LULC type in the catchment was used in the analysis. In addition, MODIS MOD11A2 land surface temperature (LST) data with a spatial resolution of 1 km in the catchment were downloaded to investigate its relationship with drought, and the MOD13A2 normalised difference vegetation index (NDVI) data with a spatial resolution of 1 km in the catchment were included to investigate the changes of vegetation with potential links to droughts. All ERA5, LULC, LST and NDVI data in the lake catchment from 2000 to 2019 were downloaded through the Google Earth Engine (GEE) platform. Links of the data and the GEE code used for data download are provided in Table S1 in supplementary.

2.3. Data analysis

Daily lake mean Chl-*a* and turbidity were calculated from the pre-processed Chl-*a* and turbidity daily satellite images in section 2.2, and monthly mean Chl-*a* and turbidity time series during the period of 2002–2019 were then aggregated from daily values. All downloaded meteorological, SPI, LST and NDVI data were firstly averaged for the catchment and then aggregated to monthly mean values to generate time series data from 2000 to 2019. Anomalies of air temperature, wind speed, precipitation, and NDVI were calculated as the difference between monthly value and the median value between 2000 and 2019.

To determine the relationship between SPI and water level, the cross-correlation analysis was applied to the SPI and water level timeseries using the "ccf" function in R language, which returned the correlation coefficients (r) with water level timeseries shifted in different months. MEI, air temperature, LST, wind speed and precipitation in the lake catchment were used to quantitatively determine which factors influenced droughts based on the boosted regression tree (BRT) method. Air temperature, wind speed, precipitation and LULC data in the lake catchment were used to explain the variations of Chl-*a* and turbidity in the lake based on BRT. BRT was used because it can handle different data types, missing values, outliers, and the interaction effects between predictors, which is very useful in fitting complex nonlinear relationships (Elith et al., 2008). The R package "gbm" was used to carry out BRT fitting in this study. BRT models with the combination of different learning rate (0.0001–0.015), tree complexity (2–4) and bag fraction (0.5–0.75) were tested, and the BRT model with the best performance in terms of training correlation, cross validation correlation and residual was finally used (Elith et al., 2008). The full data processing and analysing process are shown in Fig. 2.

3. Results

3.1. Variations of water level and water quality

Water level showed substantial variations between 2000 and 2019 in Lake Qadisiyah. Four periods of significant declines in water level were identified which are indicated with a grey shaded area in Fig. 3a. In these periods, water level was continuously lower than the average value (138.3 m) for at least six months. Period one spanned from September 2000 to December 2001 with the lowest water level of 132.9 m in December 2001. Period two was from August 2008 to December 2011 with the lowest level of 120.3 m in August 2009. The overall lowest water level was observed in period three between November 2014 and March 2016 with the lowest level of 120.0 m in July 2015. Finally, period four spanned from August 2017 to February 2019 and showed the lowest water level of 123.7 m in November 2018. The average Chl-*a* was 6.3 mg/m^3 and it showed an overall increasing trend between 2000 and 2019, clearly higher values were observed in 2008–2010 with the maximum value of 12.8 mg/m^3 in October 2009, and 2016–2019 with the maximum value of 14.4 mg/m^3 in January 2019 (Fig. 3b). The average turbidity was 3.6 NTU in the study period, but extremely high values were observed in 2009 with the highest turbidity of 17.9 NTU in March 2009, and in 2017–2018 with the highest turbidity of 14.2 NTU in October 2018 (Fig. 3c).

Both annual mean Chl-*a* and turbidity were higher in the western part of Lake Qadisiyah, where the inflow from the Euphrates River is, than those in the eastern part of the lake, where the dam is located (Fig. 4 and Fig. 5). Using 42.2 °E as the west-east boundary, the average turbidity during the study period was 3.5 NTU in the eastern lake

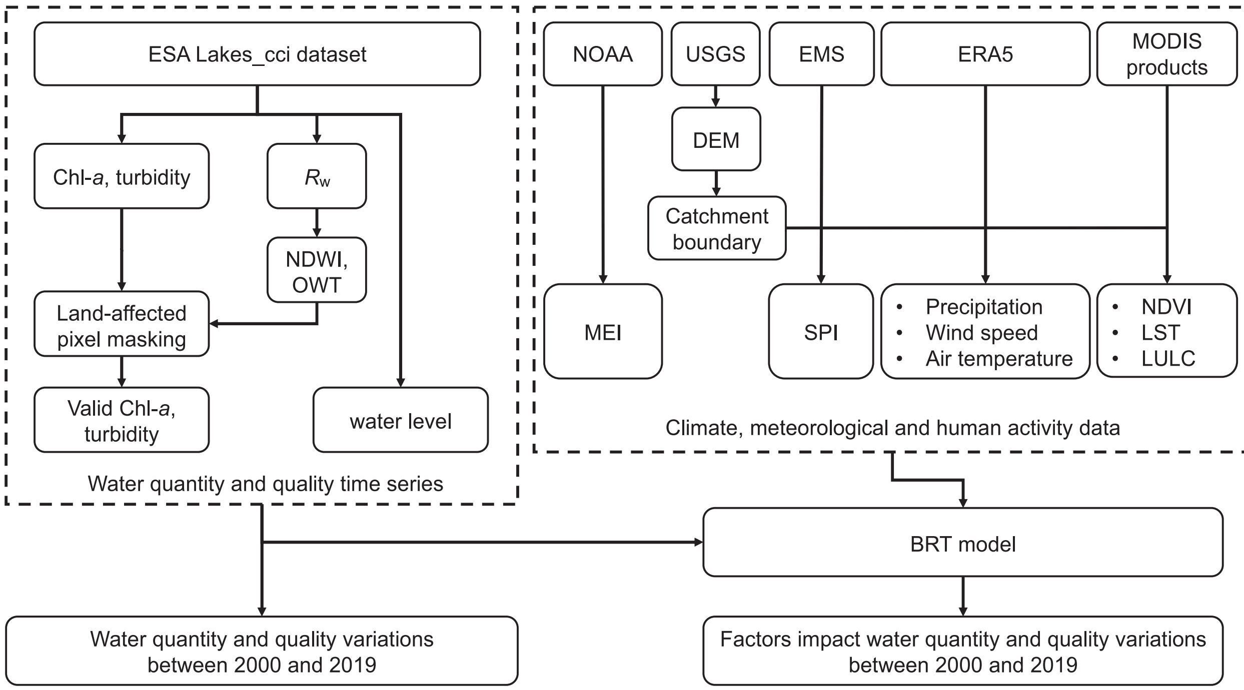

Fig. 2. Flowchart of data collection, processing and analysis.

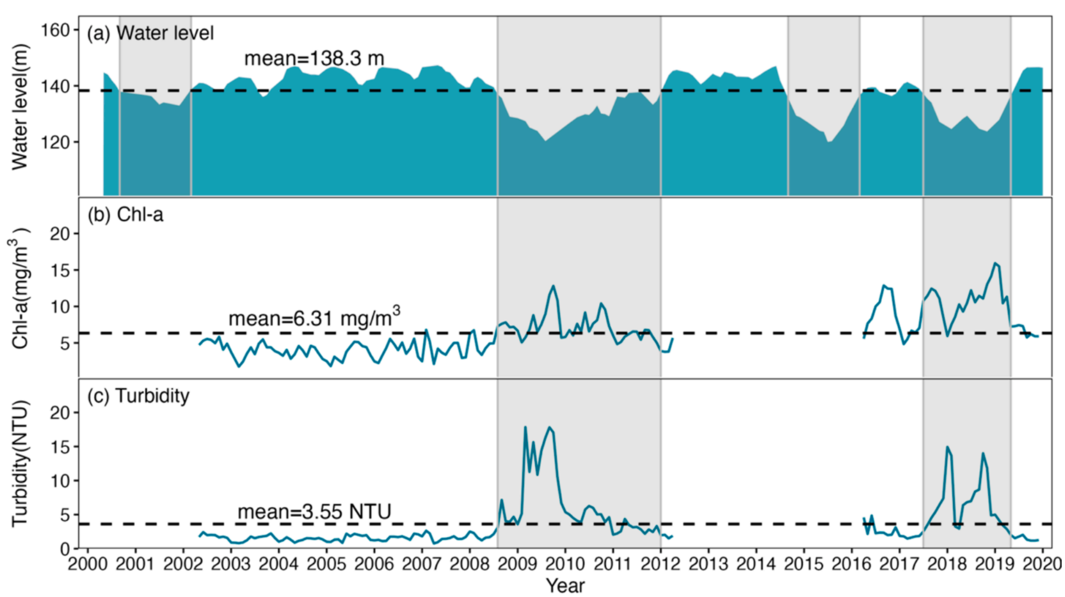

Fig. 3. Changes of water level, Chl-*a* and turbidity during the period 2000–2019 in Lake Qadisiyah, Iraq. Grey shaded areas indicate water levels lower than the average in the past twenty years. Black dashed lines are the mean values of water level, Chl-*a* and turbidity during 2000–2019.

compared to 9.4 NTU in the western lake. In terms of interannual changes, Chl-*a* in 2008–2011 and 2016–2019 were higher than in other years (Fig. 4g–j and l–o). Turbidity was higher in 2008–2010 and 2018 compared to other years (Fig. 5g–i and n). In addition, a smaller water surface area was observed in 2009 and 2018 compared to other years (Fig. 4h, n, 5h, n). The smallest water area was observed in 2009 at 146.9 km^2, which was 35 % of the maximum area in 2004 at 418.0 km^2.

3.2. Variations of meteorological factors in the catchment

Monthly mean air temperature between 2000 and 2019 varied from a maximum of 29.0 °C in July to a minimum of 3.1 °C in January in the catchment. The mean air temperature in 2001, 2010, and 2014–2019 was higher than other years (teal area in Fig. 6a). Colder winters were found in 2007 when the air temperature reached −1.0 °C in January, and in 2016 when the value was 2.0 °C in January. These values were lower than the average air temperature in January of the past twenty years (black dashed line in Fig. 6a). Warmer winters were found in 2009 and 2017, with air temperature of 6.0 °C and 5.6 °C in January respectively.

Monthly total precipitation in the catchment showed higher values in winter than in summer, with the maximum of 5.6 cm in January and minimum of 0.5 cm in August. Extremely low precipitation values were found in the period of 2007–2009 (black arrow in Fig. 6b), with the lowest yearly mean precipitation of 2.3 cm in 2008, followed by the second lowest precipitation in 2017 (2.5 cm, black arrow in Fig. 6b).

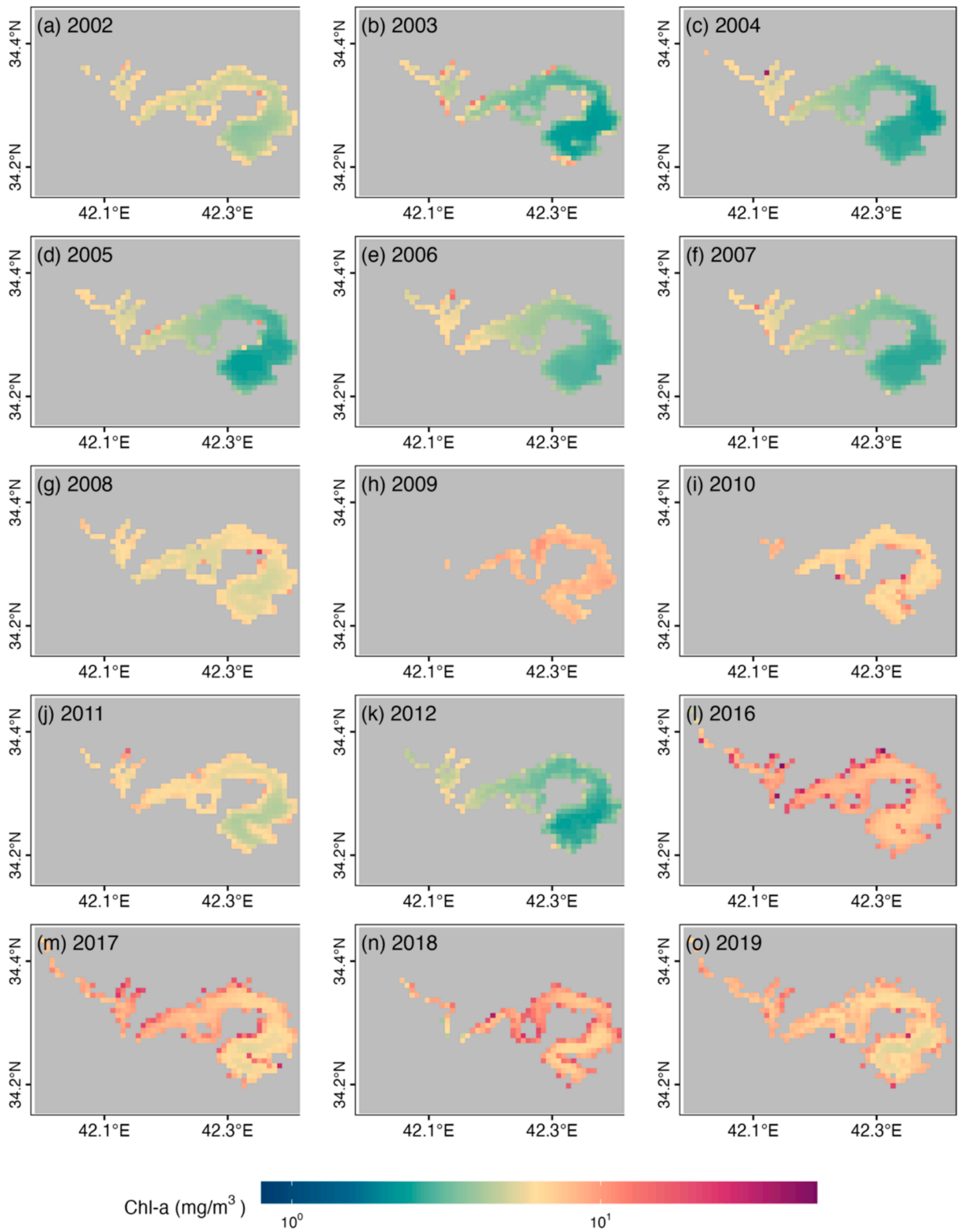

Fig. 4. Spatial distribution of annual mean Chl-*a* concentration in Lake Qadisiyah, Iraq.

Higher precipitation was found in 2003, 2006, 2012, and especially 2018–2019.

Wind speed showed higher values in summer than in winter, with the highest monthly average wind speed of 3.2 m/s in July and lowest of 0.3 m/s in November. Mean wind speeds in 2003, 2004, 2008 and 2013 were higher than that in other years, while in the most recent five years it was lower than average. Wind speeds in July of 2003, 2008, 2009, 2013 and 2014 were each higher than the average of July wind speed (black dashed line in Fig. 6c).

3.3. Variations of climate factors in the catchment

By using a MEI threshold of ± 0.5, four warm events (WE) were found which lasted longer than six months in the past twenty years (Fig. 7a). WE1: August 2002 to March 2003 (8 months, Max MEI: 1); WE2: August 2006 to January 2007 (6 months, Max MEI: 0.9); WE3: October 2009 to April 2010 (7 months, Max MEI: 1.3); and WE4: May 2015 to May 2016 (13 months, Max MEI: 2.2). During the study period, there were also five cold events (CE) that lasted longer than six months. CE1: January 2000 to June 2001 (16 months except for August and September 2000, Min MEI: −1.4); CE2: October 2005 to April 2006 (7 months, Min MEI: −0.8); CE3: June 2007 to May 2009 (24 months, Min MEI: −1.5); CE4: June 2010 to March 2012 (22 months, Min MEI: −2.4); and CE5: July 2017 to June 2018 (12 months, Min MEI: −1.3). Cold events generally lasted longer and they were more severe than warm events. For example, the cold event during 2007–2009 lasted 24 months continuously with 11 months of MEI lower than −1.0, while the cold event during 2010–2012 lasted 22 months including 18 months with

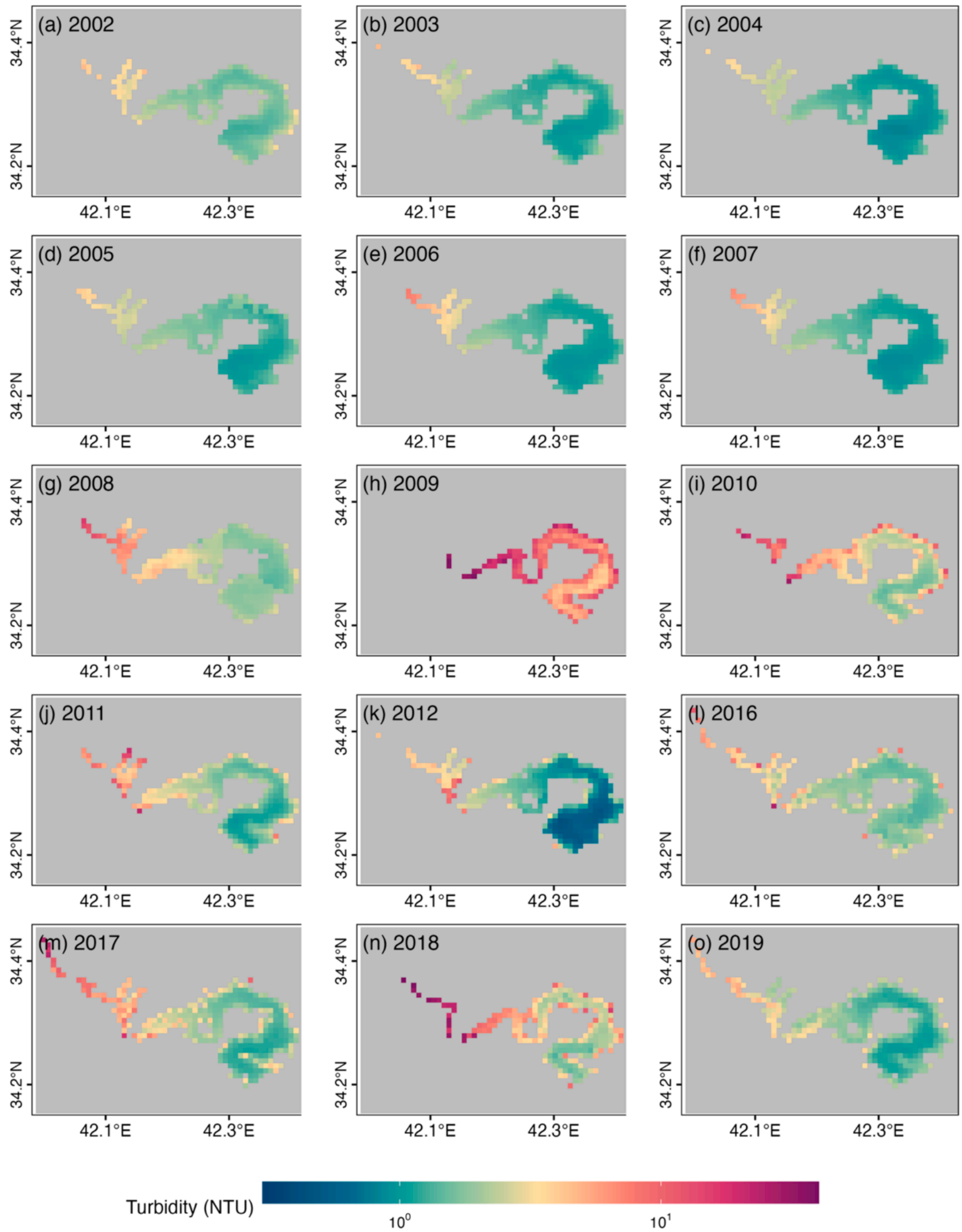

Fig. 5. Spatial distribution of annual mean turbidity in Lake Qadisiyah, Iraq.

MEI lower than −1.0.

In the catchment of Lake Qadisiyah, four drought events (DE) were identified with SPI values lower than −1 (red area in Fig. 7b). DE1: January 2000 to September 2000 (except for May 2000, 8 months, Min SPI: −1.2); DE2: March 2008 to February 2009 (12 months, Min SPI: −1.6); DE3: January 2011 to March 2011 (3 months, Min SPI: −1.4), and DE4: December 2017 to April 2018 (except for February and March 2018, 3 months, Min SPI: −1.4). An SPI higher than 1 only occurred in December 2018 to October 2019 (11 months, Max SPI: 1.8). In addition, we found that the SPI values in 2007–2018 (mean: −0.34) were lower than that in 2001–2006 (mean: 0.30), with more negative and less positive values.

By comparing MEI and SPI timeseries, it was found all four droughts co-occurred with cold events (shaded areas in Fig. 7a and b). The most severe and longest drought in 2008–2009 corresponded to the longest cold event in 2007–2009 (CE3). After each drought event, there was a drop in water level (shaded area in Fig. 7c). There was an additional period of water level decrease in 2014–2016, which was not preceded by a decrease in MEI below −0.5 or in SPI below −1.0.

3.4. *Change of vegetation in the lake catchment*

NDVI in the lake catchment were clearly lower in 2000, 2008, 2012 and 2017, and higher in 2001, 2010, 2013–2015 and 2019, compared to other years (Fig. 8). When comparing the NDVI anomalies to the SPI timeseries in Fig. 7b, it was found that NDVI in march in those years when droughts happened (red circles in Fig. 8) showed very low values, and no obvious low NDVI was found in the year of 2014–2016. This

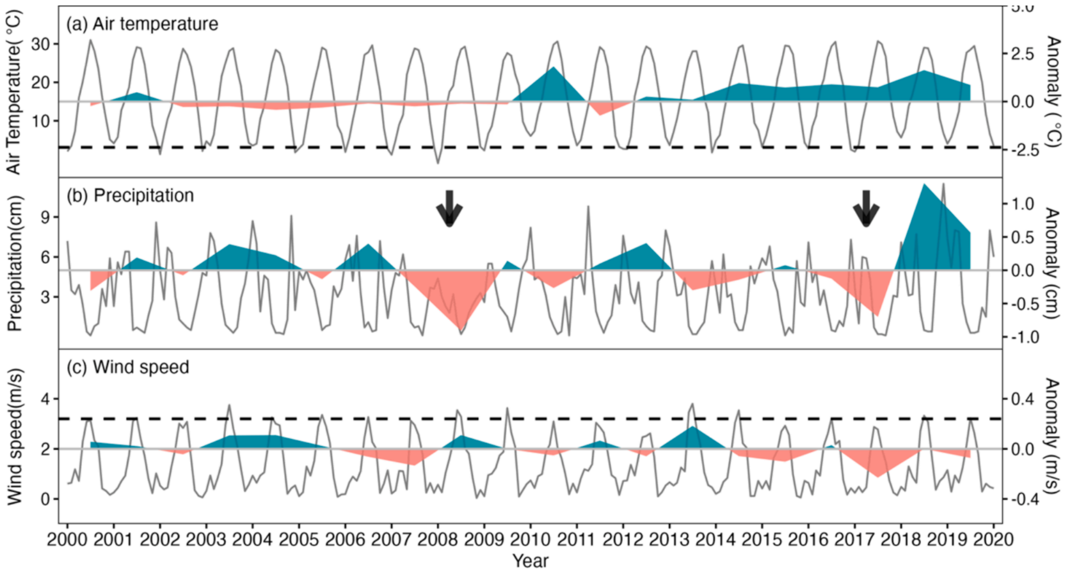

Fig. 6. Catchment-averaged air temperature, monthly total precipitation, and wind speed for Lake Qadisiyah during 2000–2019 from ERA-5 data. Black dashed lines are the mean air temperature in January in 6a, and the mean wind speed in July in 6c. Red and teal areas are the anomalies of yearly median values. Black arrows indicate the two periods where precipitation was extremely low. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

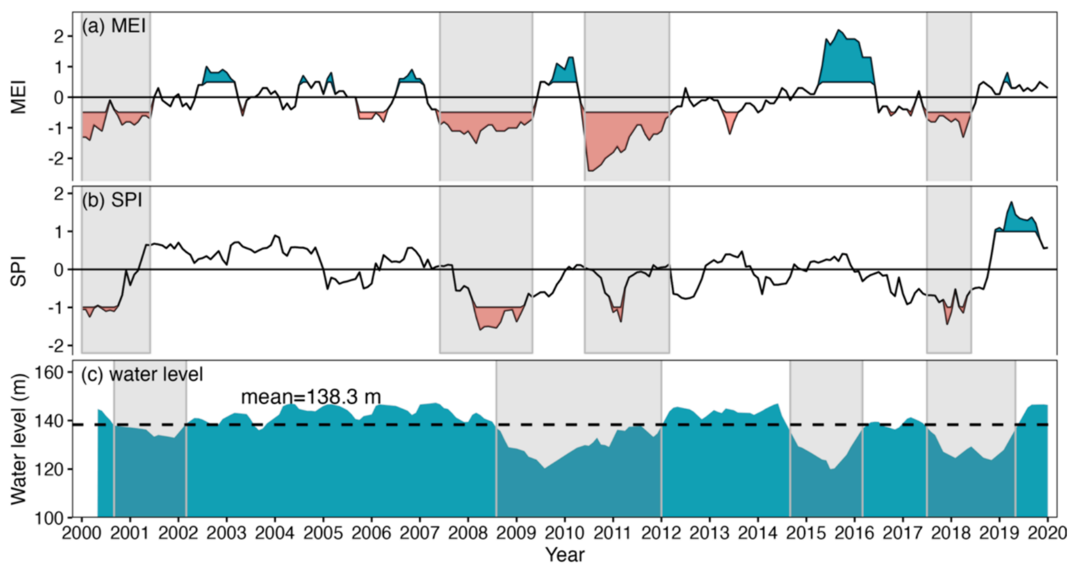

Fig. 7. ENSO index (MEI), drought index (SPI) in Lake Qadisiyah catchment, and water level of Lake Qadisiyah during 2000–2019. Red and teal areas indicate cold and warm events respectively in 7a. Red and teal areas indicate dry and wet periods respectively in 7b. Grey shaded areas indicate cold periods in 7a and 7b, and extremely low water level in 7c. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

further indicates that water level decrease in 2014–2016 was probably not caused by climatic variability as other cases.

3.5. Changes of land use land cover in the catchment

Bare land dominated the land use land cover type in Lake Qadisiyah catchment with an average percentage of 45.25 % for the study period, followed by shrub & grassland (36.98 %), and cropland (16.52 %) (Fig. 9). There were only small areas of forest (<0.1 %), built-up (0.61 %) and water bodies (0.64 %) in the catchment. Water area in the Lake Qadisiyah catchment showed similar changes to the water level changes in Lake Qadisiyah in the study period with remarkable decreases in 2001 (0.62 %), 2009 (0.59 %), 2015 (0.62 %) and 2018 (0.60 %). The cropland area also showed low values in 2008 (14.35 %), 2009 (14.87 %), 2017 (15.47 %) and 2018 (16.08 %). Built-up area in the catchment continuously increased in the study period. Bare land and forest area showed a slight increase, and shrub & grassland area showed a decreasing trend in the study period.

3.6. Drivers of drought, water level and water quality changes

MEI explained 67.5 % of SPI variations in the Lake Qadisiyah catchment, and showed a significant negative relationship ($p < 0.01$) as in Fig. 10a. Lower SPI values normally appeared when MEI was low, which means La Niña coincided with drought events in the lake catchment. Precipitation was the second most important factor but only contributed 18.6 % to SPI variations in the catchment, with low SPI values (drought) occurring when precipitation was low (Fig. 10b). It

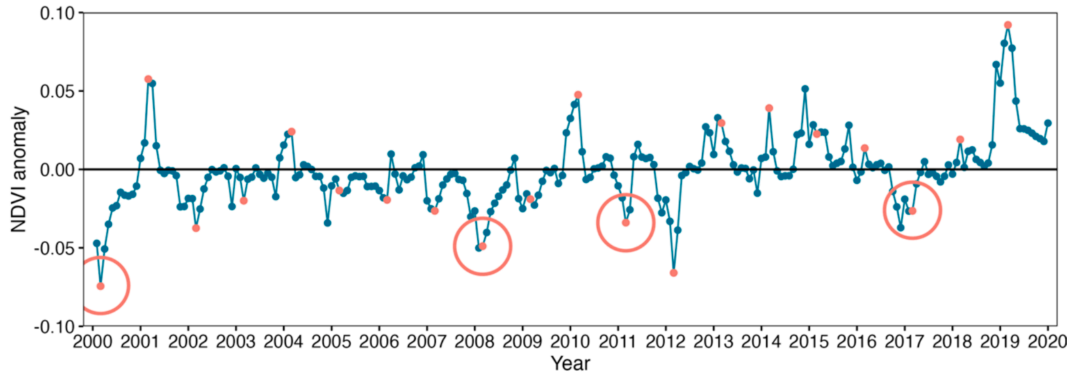

Fig. 8. NDVI anomalies in Lake Qadisiyah catchment. Red points represent NDVI in March, the four red circles indicate the four drought events between 2000 and 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

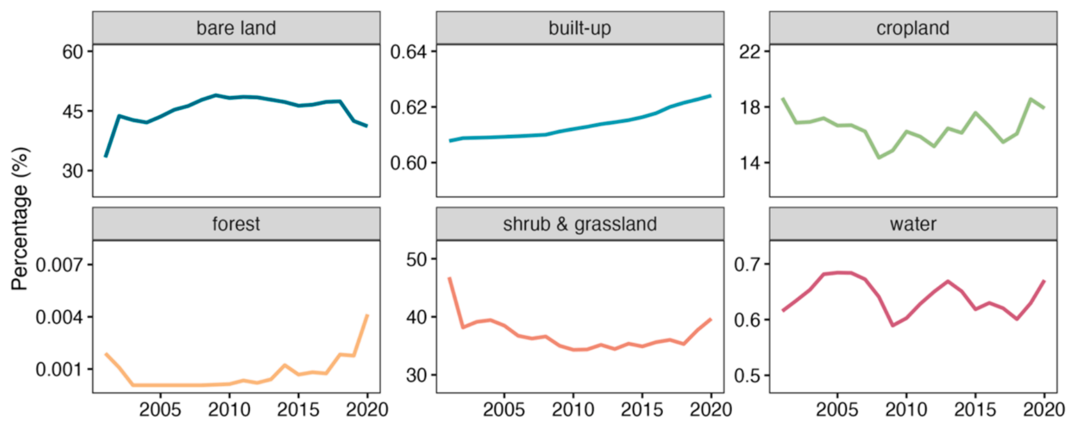

Fig. 9. Land use land cover type changes in the catchment of Lake Qadisiyah between 2000 and 2019.

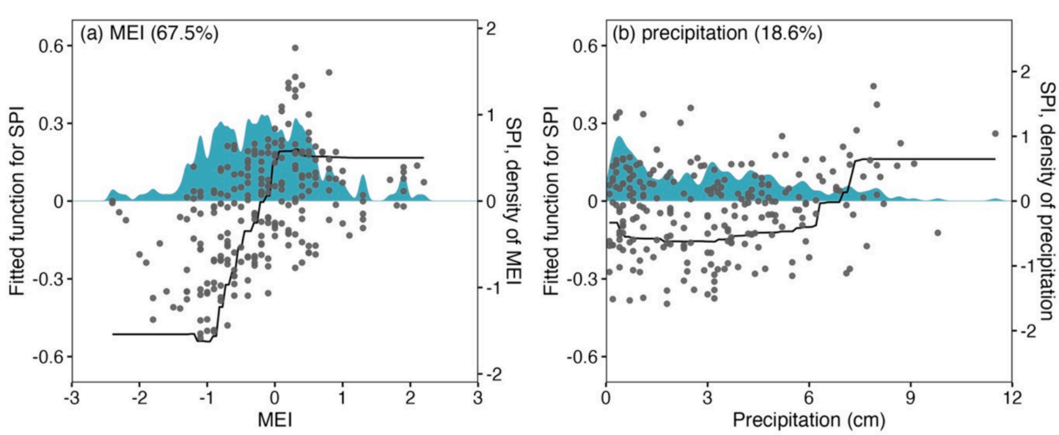

Fig. 10. Impacts of (a) MEI and (b) precipitation on drought events in the Lake Qadisiyah catchment. The solid line is the fitted function of MEI or precipitation on drought events, grey dots are the monthly SPI and teal area is the density of MEI or precipitation during 2000 and 2019.

should be noted that SPI was calculated from precipitation, this infers that MEI was the main factor leading to drought in the lake catchment.

The decrease in water level happened after an SPI decrease as shown in Fig. 7b and 7c. The cross-correlation analysis revealed that water level and SPI time series have a maximum correlation with a lag of 10 months (Fig. 11a), and they showed a significant positive relationship with $r = 0.61$ ($p < 0.01$, Fig. 11b). This means after a long-term drought happened in the catchment, water level in the lake typically decreased to a minimum 10 months later, such as the severe droughts in 2008 and 2017 in Fig. 7b. For all water bodies in the lake catchment, a similar relationship between water area with SPI was found with $r = 0.60$ but a shorter lag of 7 months (Fig. 11c).

Water level decline in 2014–2016 did not associate with any SPI or NDVI decrease (Fig. 7 and Fig. 8), reports documented that water was weaponised during militant conflicts in Iraq, particularly along the Euphrates River (UNEP, 2017). The battleground extended from Tabaqa dam (upstream of Lake Qadisiyah) to Fallujah barrage (downstream of Lake Qadisiyah). A mass release of water took place to impede militants from attacking the Haditha dam. As a consequence, an increase of river area was observed downstream of Lake Qadisiyah, and an increase of surface area in Lake Razaza (located downstream of Lake Qadisiyah) was reported in 2014 (Hasan et al., 2019). In addition, the water flow to

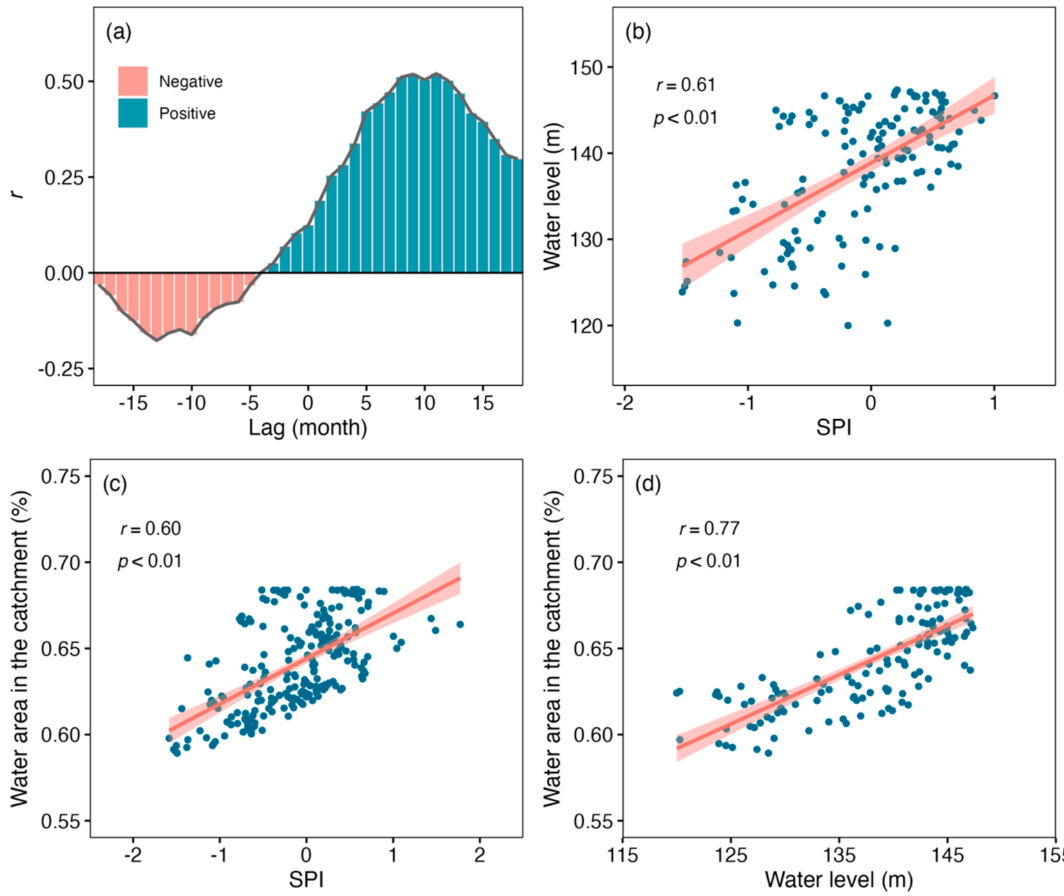

Fig. 11. Relationship between water level in Lake Qadisiyah, water area in the lake catchment and SPI in the lake catchment. (a) Cross-correlation analysis between water level and SPI, colours indicate the positive and negative relationships between water level and SPI. (b) Relationship between water level and SPI after shifting the timestamp of SPI to 10 months later. (c) Relationship between SPI and water area in the catchment after shifting the timestamp of SPI to 7 months later. (d) Relationship between water level in Lake Qadisiyah and water area in the catchment.

Iraq in the Euphrates River was cut off from March to October 2015 (UNEP, 2017), which means no water flowed into Lake Qadisiyah.

Built-up area and water area changes in the catchment were the two main factors associating with Chl-*a* changes in Lake Qadisiyah, with a relative contribution of 29.2 % and 28.6 % respectively (Fig. 12a and b). In addition, cropland area change was the third factor relating to Chl-*a* variations in the lake but with a relatively small contribution of 11.2 %. Other factors have very weak impacts with relative contribution <10 %. An increase in built-up area and crop land area, a decrease in water area in the catchment tended to appear higher Chl-*a* in the lake. For turbidity variation, water area change in the catchment was the main factor with a high contribution of 55.3 %, and lower water area associated with higher turbidity (Fig. 12c). Shrub and grassland change was the second influencing factor but its contribution was only 8.9 % (Fig. 12d). Other factors had relatively weak impacts (<10 %) on turbidity variation. It should be noted that water area variation in the catchment was highly related to the water level in Lake Qadisiyah (r = 0.77, p < 0.01, Fig. 11d), because all other water bodies are located at upstream in the catchment providing inflow to our study lake, and water area changed far more in Lake Qadisiyah than other lakes in the catchment.

4. Discussion

We observed remarkable changes of water level, Chl-*a* and turbidity in Lake Qadisiyah between 2000 and 2019 from satellite data, with water level decreasing and Chl-*a* and turbidity increasing especially in the periods of 2008–2010 and 2017–2018. By analysing meteorological and climate data, we found that water level changes were connected to the occurrence of droughts (p < 0.01) within the lake catchment. Droughts were also followed by a drop in water level, with an overall lag time of 10 months (Fig. 11). Droughts were found to be mainly associated with cold events (La Niña, relative contribution: 67.5 %) with decreased precipitation in the catchment (Fig. 6b, Fig. 10). Less water inflow from the catchment during droughts, together with continued or greater water usage to mitigate the shortage of water for irrigation and hydropower generation had the combined effect of the water level decline reaching its minimum level after around 10 months. Previous research in the study area reported that La Niña events can lead to a north-easterly moisture flux which brings less moisture and leads to decrease of precipitation in this area (Mariotti, 2007). Research in other areas (e.g., reservoirs in US, Brazil) also reported that droughts can lead to water level decline and water quality deterioration in lakes (Olds et al., 2011; Mosley et al., 2012; Mosley, 2015; Watanabe et al., 2016; Brasil et al., 2016). These findings emphasize the crucial impacts of climate on lake environment especially for those in semi-arid and arid regions.

Chl-*a* showed an overall increasing trend with high values in 2008–2010 and 2016–2019 in Lake Qadisiyah (Fig. 3). Our analysis revealed that Chl-*a* increase was mainly associated with the increase of built-up area and decrease of water area in the catchment. Built-up area is highly linked to human activities and population, its increase may have led to more nutrient discharge in the catchment and finally flow to the lake supporting the growth of phytoplankton. Water area decrease in the catchment may have several impacts on water quality in Lake Qadisiyah. First, reduced inflow from the catchment can increase the impact of nutrients from point sources (industrial, agricultural and

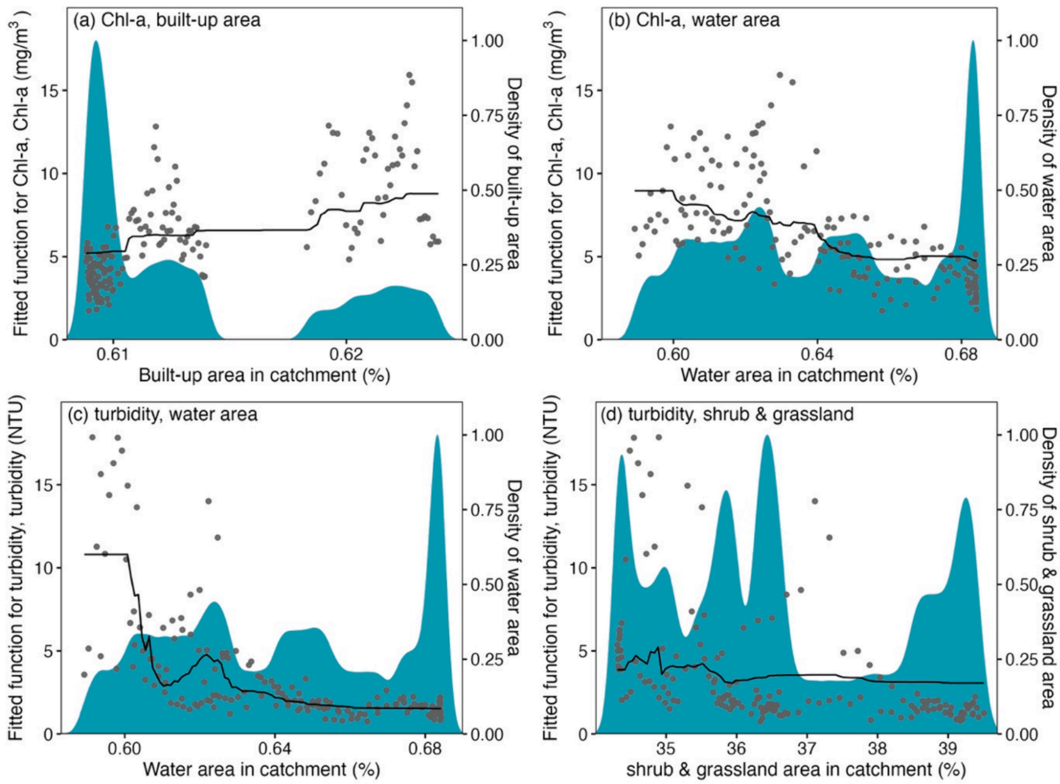

Fig. 12. Relationship between (a) built-up area, (b) water area in the catchment and Chl-*a* in Lake Qadisiyah. Relationship between (c) water area, (d) shrub & grassland area in the catchment and turbidity in Lake Qadisiyah. Solid lines are the fitted functions of factors on Chl-*a* or turbidity variations. Dots are the monthly Chl-*a* or turbidity. Teal areas are the density of each factor in the graph.

domestic wastewater) because of the lack of dilution water (Van Vliet and Zwolsman, 2008). Lower water level in the lake can lead to higher nutrients release from the sediments (Mosley et al., 2013; Watanabe et al., 2016), and a drier atmosphere can lead to more atmospheric deposition to the lake (García-Jurado et al., 2012). Those may have increased the nutrients in Lake Qadisiyah for phytoplankton growth. Second, shallower water and higher air temperature during drought can cause higher water temperature (Hrdinka et al., 2012), which favours phytoplankton growth such as cyanobacteria (Paerl and Huisman, 2008). In addition, increased water retention time because of less inflow from rivers, stronger stratification because of higher air temperature during drought can also promote phytoplankton growth in the lake (Mosley, 2015). These results suggest that measures to deal with both extreme events and pollutions are needed to prevent water quality deterioration in the lake.

Turbidity variations were mainly associated with water area changes in the catchment, which was also significantly correlated with water level changes in the lake ($r = 0.77$, $p < 0.01$). Smaller water areas in the catchment tended to have higher turbidity. This may be because lower water level in the lake can lead to more sediment resuspension, and more turbid water from rivers as river water also become shallower with more mixing between water and sediments (García-Jurado et al., 2012; Mosley et al., 2013; Mosley, 2015). Previous research also reported that drought-induced lake water level decrease can lead to higher turbidity (Olds et al., 2011; Brasil et al., 2016).

In addition, we observed water level decrease during 2014 and 2016, which led to the lowest water level of 120.0 m in July 2015 in Lake Qadisiyah (Fig. 3). The above-mentioned analysis could explain the decrease of lake water level in 2000–2001, 2008–2010 and 2017–2018. However, there were no combined drought and cold event found in 2014–2016 (Fig. 7a, b). Precipitation in the catchment did not show large anomalies in 2014–2016 (Fig. 6c). NDVI can indirectly reflect water availability in the catchment as vegetation is sensitive to drought in semi-arid area (Barlow et al., 2016; Daham et al., 2018), and it was reported that NDVI in March/April can best reflect precipitation in winter and temperature in spring in this area (Daham et al., 2018; Alhumaima and Abdullaevz, 2020). But NDVI did not show any decrease in the year of 2014–2016 (Fig. 8). The reported military conflicts with water flow cut off in upstream from March to October 2015, and water release from the Haditha dam with a result of water area increase in downstream of Lake Qadisiyah in 2014 (UNEP, 2017; Hasan et al., 2019) seem to explain the observed water level decrease in 2014–2016. The time line of water flow cut off in upstream matches very well with the time of observed lowest water level in July 2015 (120.0 m, Fig. 7c).

It is projected that the frequency and intensity of droughts will increase (IPCC, 2021), the precipitation will decrease in Iraq in the future (Osman et al., 2017; Al-Mukhtar and Qasim, 2019), along with other pressures from society such as population increase and inefficient water use, those will likely lead to challenges in water resource availability in this region. This study filled the knowledge gaps of how droughts impacted water quantity in the lake, which can support dam centres or local water sections making more efficient water use strategies, establishing more water storages and improving transboundary cooperation with neighbouring countries to avoid water crisis in the future. Our study also revealed the highly correlation between water quantity and quality in this lake, and the impacts of human activities in the catchment on water quality. That means water quality will likely become worse in the context of decreasing water availability and increasing population in the lake catchment in the future. This provides a warning to the water sections, and actions for improving water qualities such as introducing pollution control measures in the catchment are recommended.

This study was carried out based on satellite observations without *in situ* data because of the difficulty of carrying out field surveys in Lake Qadisiyah. Future studies with inclusion of field-observed data, especially during drought events, can be carried out to further validate the findings in this study. The impacts from conflicts on water level in the lake were not possible to be quantified in this study, further investigations by including data such as water flow and water release records from the dam centre where possible will be helpful. Storm is another potential factor which may bring dusts to the lake leading to high turbidity, which need to be considered in future researches. There were some water quality data gaps in 2013–2015 because of the unavailable MERIS and OLCI images in those years, filling those gaps using other satellite images such as MODIS will be useful to further confirm the relationship between water quality and water level.

5. Conclusions

This study demonstrated the use of satellite data in investigating water quantity and quality variations in Lake Qadisiyah, Iraq during 2000 and 2019, where the long-term *in situ* monitoring data were not available. The results proved the capability of Earth observation, and it can be a useful and reliable approach in monitoring and understanding long-term lake water environment changes. This study also confirmed the compounding effects of extreme events and human activities from the lake catchment on water quantity and quality in the lake, where water level changes in the lake were mainly associated with La Niña-induced droughts in the catchment, Chl-*a* and turbidity variations in the lake were associated with water area changes in the catchment because of droughts. Human activities including control of dam such as releasing and cutting off waters, and built-up area increase in the catchment also presented impacts on water qualities in the lake. Those findings emphasize that lake water environments in semi-arid regions are impacted by both climate and human activities in the catchment, they should be carefully considered when making future water management strategies and decision-making in Iraq or similar semi-arid regions to deal with potential water crisis and water quality deterioration.

CRediT authorship contribution statement

Dalin Jiang: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ian Jones:** Writing – review & editing, Investigation. **Xiaohan Liu:** Writing – review & editing, Data curation. **Stefan G.H. Simis:** Writing – review & editing, Investigation. **Jean-François Cretaux:** Writing – review & editing, Data curation. **Clement Albergel:** Writing – review & editing, Investigation. **Andrew Tyler:** Writing – review & editing. **Evangelos Spyrakos:** Writing – review & editing, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data can be accessed from the link provided in the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2024.104021.

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