Water Quality Monitoring Using Landsat 8 and Sentinel-2 Satellite Data (2014–2020) in Timsah Lake, Ismailia, Suez Canal Region (Egypt)

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Abstract
The present study aims to monitor the water quality in Timsah Lake by satellite data, the largest water body in Ismailia district, Egypt. To achieve this, multi-temporal space-born data of both Landsat-8 OLI- (L1 and L2) and Sentinel-2 (2A and 2B) were used during 2014–2020. The methodologies of Case 2 regional coast colour algorithm and aquatic reflectance were applied for monitoring the physical properties of different water characteristics encompassing chlorophyll-a, total suspended matter (TSM), and aquatic reflectance. Satellite data from dry and wet seasons (2014–2020) were selected to examine seasonal and temporal variation. Comparing water quality through the dry and wet seasons (2014–2020) is to avoid the difference in atmospheric conditions and detect seasonal variations. The present study results have shown that the Western Lagoon and its streams are considered the primary source of pollution. Specifically, lower values are observed during August 2015 for TSM (4–17 g m\(^{-3}\)) and chlorophyll-a (2–11 g m\(^{-3}\)), while the highest values of TSM (23–50 g m\(^{-3}\)) appear during August 2018 and for chlorophyll-a during August 2016–2018 (20–40 g m\(^{-3}\)). For the wet season for TSM, the lowest values are observed during 2016 (3–10 g m\(^{-3}\)), and the maximum is noticed during 2019 (13–29 g m\(^{-3}\)); for the chlorophyll-a, maximum values are observed during 2017 (10–23 g m\(^{-3}\)).

Keywords Total suspended matter (TSM) · Water quality · Chlorophyll-a · Landsat 8 · Sentinel-2 · Timsah Lake-Ismailia

Introduction
The Timsah Lake, during the recent decades, has been changing rapidly due to human and environmental activities such as fishing, tourism, agricultural drainage returns flows, and industrial waste discharges. As a result, it is mandatory to monitor the area’s water quality. Within the framework of increasing world trade, increases in the size of ships, and the need for the Egyptian economy to develop its resources, it was mandatory to expand the current Suez Canal (SC) to cope with the increasing future world trade crossing Egypt to other countries. (EEAA, 2014). The New Suez Canal (NSC) was implemented on the 5th of August 2014 parallel to the existing one. One year later, the NSC was opened on the 6th of August 2015, where 76,000 km\(^2\) on either side of the canal are to be developed for tourism enterprises, industrial and technology estates. Another notable change concerns the building of the new Ismailia city on the eastern bank of the canal, covering an area of about 16,500 acres for the habitation of about 500,000 population. Lake Timsah is located in the city of Ismailia and communicates directly with the NSC.

The NSC is 72 km long, including 35 km of dry digging and 37 km of expansion and deep digging to provide a second shipping lane allowing separated passing of ships in opposite directions.

Space-born data hold a significant role in monitoring and assessment of lakes water quality (Sudheer et al., 2006; Politi et al., 2015; Shuchman et al., 2017; Blix et al., 2018;
Nouromand-Jadidi et al., 2019; Song & Wang, 2019; Papenfus et al., 2020; Wang et al., 2020; Xu et al., 2020; Wang et al., 2021). The difference in reflectance at various wavelengths is mainly attributed to physio-chemical characters of water representing the different water quality parameters. Thus, remote sensing enables to monitor water quality indicators of freshwater ecosystems. In the last few years, remote sensing has become one of the essential valuable tools for detecting and monitoring phytoplankton features comprising chlorophyll-a, total suspended matter (TSM), and coloured dissolved organic matter (CDOM). Generally, two models of remote sensing data refer to water quality. The first method is empirical and purely statistical, and the second method is semi-analytical. The models depend on the interaction between light and the water surface, particularly in the visible light of the electromagnetic spectrum. According to the first approach, the visible part of the electromagnetic spectrum plays an important role in the detection of water quality indicators, specifically chlorophyll-a and TSM. Recent studies demonstrated the usage of the second approach where many algorithms for detecting and monitoring the different water quality parameters are used, e.g. (Saberoon et al. 2020; Greeling et al. 2020; Sahoo et al. 2020; and Chawla et al. 2020). These algorithms elucidate a sensitivity reduction to noisy data and atmospheric effects. In the present study, the two approaches have been carried out depending on utilising visible and near-infrared bands for applying the first approach and the C2RRC algorithm for the second one, which will be explained in the methodology section.

In the summer months, Ismailia city and its surroundings are characterised by intensive human activities due to tourism, including marine navigation, which has a close relationship with the pollution in Lake Timsah. This study aims to detect water quality changes in TSM and chlorophyll-a of Timsah Lake using the two approaches of remote sensing techniques in detecting and monitoring water quality: semi-analytical and empirical modelling during the period 2014–2020 in dry and wet seasons. The study was based on both Sentinel-2 and Landsat 8 data. Two different datasets were used to cover the time before the construction of the NSC.

The Study Area

Timsah Lake is considered one of the most important lakes in Egypt due to its strategic location on the Suez Canal. The SC is the main route joining the African continent with Asia and Europe from Suez City, in the south of the Suez Canal, to Port-Said City in its northern tip (Fig. 1). The area also results in many human activities encompassing marine navigation, as a pathway for trading ships with other countries and fishing which provides a vital source of food and income for local population and tourism.

The study area can be subdivided into three basins: Lake Timsah, the Western Lagoon, and the Suez Canal pathway. Timsah Lake has a nearly triangular shape with elongated sides extending roughly WNW-ESE direction. The lake’s surface area is about 15 km², and the maximum depth is 6 m in the western part, increasing to 20 m in the eastern part. The lake receives both fresh and saline water; the freshwater is mainly drained from the outflow of fresh Ismailia Canal in addition to other drains like El-Forsan, El-Mahsama, and Abu-Gamous (El-Sherbiny et al., 2011). On the other hand, the high saline water comes from the Suez Canal, whereas the brackish water comes from the Western Lagoon into the Lake. Finally, it is essential to mention that the lagoon receives domestic and agricultural wastewaters mainly from El-Mahsama and Abu-Gamous drains. Accordingly, Lake Timsah suffers from domestic pressure such as sewage pollution, herbicides, and pesticides (ETPS, 1995).

In recent years, Timsah Lake suffered from dangerous rates of pollution, which may be attributed to different causes; mainly anthropogenic activities due to the rapid growth of population activities in recent years around Timsah Lake, such as shipbuilding and maintenance, municipal wastewater dumping off, and agricultural drainage loading in the lake, have significantly increased the eutrophication and pollution rates of the lake (Kaiser et al., 2009; Madkour et al., 2006). All the previously mentioned causes of pollution threatened, to a great extent, the lake’s purity; interfered with its recreational purpose, richness and diversity of indigenous fish, phytoplankton, zooplankton, plants and animal population (Kamel, 2013; Mehanna et al., 2016). The aquatic ecosystem of Timsah Lake recorded hazardous levels of a pollutant of various forms, heavy metals concentrations in the water, sediments, and marine fauna (Abd El-Azim, 2002; Gabr and Gab-Alla, 2008).

Satellite Data

Landsat-8 Images

Free satellite images from Landsat 8 and Sentinel-2 satellites have been exploited to analyse the objective of this research study (Table 1). Landsat 8 is a relatively recent launched Landsat satellite and carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) instruments. The products used are Level-1 (C2RCC) and Level-2 (aquatic reflectance) data for Landsat 8 obtained from the US Geological
**Fig. 1** Location of the study area (in Google Earth environment)

**Table 1** Landsat 8 and Sentinel 2 scenes used

| Satellite   | Product type | Acquisition day | Orbit     | Path, row (Landsat8) relative orbit (Sentinel-2) |
|-------------|--------------|-----------------|-----------|---------------------------------------------------|
| Landsat 8   | L1           | 2014/2/11       | Descending| 176, 39                                           |
| Landsat 8   | L1           | 22/8/2014       | Descending| 176, 39                                           |
| Landsat 8   | L1           | 2015/1/29       | Descending| 176, 39                                           |
| Landsat 8   | L2           | 06/8/2020       | Descending| 176, 39                                           |
| Sentinel-2A | L1C          | 03/8/2015       | Descending| 21                                                 |
| Sentinel-2A | L1C          | 07/8/2016       | Descending| 21                                                 |
| Sentinel-2A | L1C          | 03/2/2017       | Descending| 21                                                 |
| Sentinel-2B | L1C          | 07/8/2017       | Descending| 21                                                 |
| Sentinel-2A | L1C          | 09/1/2018       | Descending| 21                                                 |
| Sentinel-2B | L1C          | 12/8/2018       | Descending| 21                                                 |
| Sentinel-2B | L1C          | 03/2/2019       | Descending| 21                                                 |
| Sentinel-2B | L1C          | 07/8/2019       | Descending| 21                                                 |
| Sentinel-2B | L1C          | 13/2/2020       | Descending| 21                                                 |
| Sentinel-2A | L1C          | 06/8/2020       | Descending| 21                                                 |
Survey (https://earthexplorer.usgs.gov). Landsat 8 acquires about 740 scenes per day on the Worldwide Reference System-2 path/row system, with a swath overlap varying from 7 per cent at the equator to a maximum of approximately 85 per cent at extreme latitudes. Each Landsat 8 scene size is 185 km × 180 km.

**Sentinel-2 Images**

The multispectral instrument (MSI) Level-1C (L1C) Sentinel-2 scenes were downloaded from ESA’s Copernicus Open Access Hub (https://scihub.copernicus.eu). Sentinel-2 satellite mission of the Copernicus programme operation started on the 23rd of June 2015 when the Sentinel-2A satellite was launched. Sentinel-2 is a wide-swath, high-resolution, optical multispectral imaging mission. The complete mission consists of the twin satellites flying in the same orbit but phased at 180°. The Sentinel-2A has been paired with the Sentinel-2B twin satellite since its launch on the 7th of March 2017. It is designed to give a high revisit time of 5 days. This mission’s objective is to provide multispectral imagery for a wide range of applications in fields including land monitoring (e.g. agriculture, vegetation, forests, waterbodies), emergency management (e.g. natural disaster monitoring and management), climate change (e.g. glaciers and coastal monitoring), and security (e.g. border and maritime surveillance). The multispectral optical instrument (MSI) of Sentinel-2 twins satellites A & B has 13 spectral bands (VIS, NIR, SWIR) having spatial resolutions of 10 m, 20 m, and 60 m for the different spectral bands. The satellite’s orbit is sun-synchronous at 786 km mean altitude, 5 days of repeated cycle with the two satellites and spatial resolution of 10 m, 20 m, and 60 m/ pixel (depending on the band) (Drusch et al., 2012). The Level-1C product is top of atmosphere in cartographic geometry, about 600 MB covering an area of 100 × 100 km. The data are Level-1C images mostly free of cloud.

The processing has been carried out by the free and open-source software SNAP (provided by ESA), the software ENVI (provided by Harris Geospatial Solution’s), and the ArcGIS software (provided by ESRI). The ENVI application was exploited for the PCA process, and the ArcGIS software was used for the exported maps. Specifically, for the C2RCC method, we have used the SNAP software.

**Methods**

**Principal Component Analysis (PCA)**

To detect changes in Ismailia city, including the Suez Canal and the general area, Landsat 8 images have been used, and the PCA method has been applied. PCA is a technique applied to multispectral and hyperspectral remotely sensed data. PCA transforms an original correlated dataset into a substantially smaller set of uncorrelated variables representing most of the information presented in the original dataset (Jensen, 2005; Richards, 1994). Their principal component axes correspond to uncorrelated data, so it could be used as a data transform to enhance areas of local changes in multispectral satellite images (Achour et al., 2020; Bustos et al., 2011; Fung & Le Drew, 1987). In addition, PCA aims to reduce the dimensionality of the data in this case, the number of original bands, to maximise the amount of information from the original bands into the least number of principal components (Estornell et al., 2013). The original spectral bands are correlated and transformed as uncorrelated principal component images. These principal components images contain information with a physical meaning that needs to be explored based on the statistics table of eigenvector (contribution of each original spectral band to the formation of each principal component image) and eigenvalues (that means the information contained in each principal component image). It is also proven that the first three principal components may contain more than 90 per cent of the information in the original eight bands. These calculations have been widely used in remote sensing to classify land surface and change detection (Fung & Le Drew, 1987).

For the current work from the Landsat 8 subscenes (L1 products), the three bands of the visible part of the electromagnetic spectrum and the near-infrared band of both

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**Fig. 2** Flow chart of the PCA processing
dates (dated 22–8-2014 / 6–8-2020) have been selected (Fig. 2). The selection of the above spectral bands is to enhance the anthropogenic characteristics and the vegetation cover. The bands of the visible part of the spectrum help us to detect changes in the surface features, such as anthropogenic features; the near-infrared band is useful for change detection in healthy vegetation because chlorophyll reflects near-infrared light. In total, 8 spectral bands have been introduced for PCA processing, and a new set of eight image components have been generated. The first image component (PC1) corresponds to a brightness image, while the rest of the image components contain spectral information. The selection of the image component, which highlights the changes in the anthropogenic and natural environment, is based on the positive or negative ("+" or "−") contribution of the initial spectral bands of each date to generate the specific component image. In this case, the image component 2 was selected because the spectral bands dated 22/08/2014 contributed negatively (−) while the spectral bands dated 06/08/2020 contributed positively (+) based on Eigenvalues.

**Case 2 Regional Coast Colour (C2RCC) Algorithm**

The objective of this algorithm is to determine optical properties and the concentrations of constituents of case 2 waters. Case 2 water is defined as a natural water body which contains more than 1 component of water constituents, which determine the variability of the spectrum of the water-leaving radiance and is presented in coastal seas, estuaries, lagoons, and inland waters (Gitelson et al., 2008; Morel & Prieur, 1977). Optical remote sensing in the visible and near-infrared spectral region has been used to estimate various water quality parameters (Zhang et al., 2002). Chlorophyll-a and TSM are some of these parameters. Chlorophyll-a is often used for determining inland water trophic state and productivity (Gitelson et al., 2008). The concentration of TSM may be caused mainly by the remnants of inorganic materials and wastewater molecules due to the anthropogenic activities around the water body (Sulistiawati et al., 2020).

The C2RCC processor was initially developed by Doerffer and Schiller (2007) and later improved by Brockmann et al., (2016). The algorithm C2RCC is based on deep learning approaches. The algorithm is developed specifically for optically complex inland waters. It uses an extensive database of radiative transfer simulations that are inverted by a series of neural networks to calculate the atmospheric correction for satellite sensors, including Landsat-8 and Sentinel-2. The C2RCC methodology creates a synchronised Landsat-8 and Sentinel-2 virtual constellation (Brockmann et al., 2016). Using the C2RCC algorithm, 11 Sentinel 2 A & B, Level-1C products have been used and acquired by the satellite during August, January, or February months each year from 2014 to 2020 (Table 1). Also, Landsat 8 Level-1 products for August for the years 2014 and 2020 and for January or February images from 2014 and 2015 (due to the lack of Sentinel-2 images) have been processed using the C2RCC (Table 1).

The pre-processing of the Sentinel 2 1C and Landsat 8 images starts with the resampling (in this case, resample in 30 m/pixel) so both datasets (Sentinel-2 and Landsat 8) have the same spatial resolution. Then, the pre-processing continues with the creation of the subset to focus on the study area. The second step concerns the application of the C2RCC algorithm to detect the amount of seawater suspended matter and chlorophyll-a. During the algorithm development, the atmospheric correction is also included. Then, a mask was applied for values indicating clouds and adjacent shadows, thus containing only cloud-free water pixels. Then on the Landsat 8, a further mask was applied to extract only the areas surrounding the water body boundary since the C2RCC algorithm does not perform as well on the Landsat 8 data. The unit of measurement is g m⁻³, which is the gram cubic metre. The processing steps are shown in Fig. 3.

![Flow chart of the C2RCC algorithm application](Image)
Aquatic Reflectance

Aquatic reflectance products can map optically active components of the upper water column in inland and near-shore waters. The Landsat 8 provisional aquatic reflectance product is derived from Landsat 8 Level-1 (L1) reflective bands over water bodies. Top-of-atmosphere (TOA) reflectance and auxiliary atmospheric data are input to an atmospheric correction algorithm to retrieve the water-leaving radiance at visible wavelengths. The water-leaving radiances are then normalised by downwelling solar irradiance to remove the remaining effects of solar orientation and atmospheric attenuation to produce spectral remote sensing reflectance (Rrs) for visible bands (USGS, 2020). Sea watercolour refers to the hue of the water caused by the presence of tiny plants that contain the pigment chlorophyll, sediments, and coloured dissolved organic material. To detect differences in water content before the construction and operation of the NSC Landsat 8 L2 dated 22-8-2014 and 6-8-2020 have been used. The final two products have been coloured using a palette to highlight the aquatic reflectance. The scale is calculated by the Rrs (sr⁻¹), which is the water-leaving radiance (Fig. 4).

Results

Principal Component Analysis (PCA)

Concerning the results of the PCA application, the analysis of eigenvalues and eigenvectors, in combination with the interpretation of the principal components, allows us to choose the component image suitable to recognise the possible changes in the area. The first image component (PC1) contains 78.35% of the information that corresponds to the brightness image (offers information about topography). The PC2 contains 11.12% of the spectral information, and there is the difference image between the two dates, resulting from the negative contribution of the original spectral bands of the first date (2014) and the positive contribution of the original spectral bands of the second date (2020) (Fig. 5). In this PC image, the grey pixels (areas) correspond to no changes; the bright areas correspond to characteristics that exist on 2014 and black or very dark grey areas that do not exist on 2014 like the NSC. The last PC images contain little information relative to other applications and “noise” (Psomiadis et al., 2005). In this case, the first component (PC1) corresponds to the brightness image (information concerning topography and albedo), and the second component (PC2) contains spectral information related to all the various changes that took place during the period 2014–2020, while the rest of the PCs contain spectral information (Fig. 5).

C2RCC Algorithm

Total Suspended Matter (TSM)

In order to further examine the characteristics of the Timsah Lake, we looked at the water quality monitoring and the TSM concentration using the C2RCC algorithm. The resulting TSM concentration from Sentinel-2 and
Fig. 6 The total suspended matter (TSM) concentration after the C2RCC algorithm application on Sentinel-2 data for the month August for the years 2015–2020.
Landsat 8 satellites is shown in Figs. 6 and 7 and 8 and 9, respectively.

**Sentinel-2 Images** Concerning Sentinel-2 data for August, the lowest values of the TSM concentration through the years appeared during August 2015, with a range between 4 and 17 g m\(^{-3}\). Nevertheless, the higher rates are attributed to some isolated pools distributed through many localities, lying between the old and new Suez Canal, the western boundaries of NSC, and the southwestern part connecting with the Old Suez Canal (OSC). The concentration of TSM increased gradually through the following years, with a slight decrease in 2017 except in the northern part of the west canal, where the values are around 4 to 12 g m\(^{-3}\). The highest concentration was recorded in

![Fig. 7](image7.png)  
**Fig. 7** The total suspended matter (TSM) concentration after the C2RCC algorithm application on Sentinel-2 data for the months January–February for the years 2016–2020

![Fig. 8](image8.png)  
**Fig. 8** The total suspended matter (TSM) concentration after the C2RCC algorithm that was used for the processing of the Landsat 8 data during the month August for the years 2014 and 2020

![Fig. 9](image9.png)  
**Fig. 9** The total suspended matter (TSM) concentration after the C2RCC algorithm that was used for the processing of the Landsat 8 data during the months January–February for the years 2014 and 2015
August 2018, where the values were around 23 and 50 g m\(^{-3}\).

As Fig. 7 indicates, the Sentinel-2 data for the wet season (January–February) through the period 2016–2020, the lowest values are recorded during 2016, with TSM being around 3–10 g m\(^{-3}\); while the maximum of the TSM concentration is visible during 2019 with values from 13 to 29 g m\(^{-3}\) in most of the Lake Timsha. The data for the years 2017 and 2020 are worth mentioning since, from Fig. 7, it is evident that the TSM concentration is relatively high near the passage between the Western Lagoon and Timsha Lake. Also, it is observed that the rate of TSM concentration in NSC is more or less compatible with that of OSC and the central part of Timsha Lake. Along the different periods through the present study, the Western Lagoon, connected with Timsha Lake through one inlet on the western side, always recorded higher levels of TSM, except at the time of the NSC opening (August 2015), which records the lowest rates of TSM.

**Landsat-8 Images** As for the results of the C2RCC algorithm for the Landsat 8, they can be seen in Figs. 8 and 9.

For the dry season, the TSM concentration for 2014 is significantly lower than the concentration of 2020, with values around 0.01 to around 7 g m\(^{-3}\) (Fig. 8). Figure 9 shows the algorithm results for the wet season (January–February), the changes between 2014 and 2015 are minor, and the values range between 0.01 and 5 g m\(^{-3}\). The only difference is that in 2014 in the southern part of the Timsha Lake, close to the OSC, there is a small pond with higher values than in 2015. Finally, it is essential to mention that Landsat 8 image for 2015 shows no data for the NSC because it was not in full operation. Lower rates of TSM characterise the navigation pass of both OSC and NSC through the same period. The results for August of 2020 (Fig. 8) are pretty different from those exported from Sentinel-2, but still, the areas that have higher values or appear to be the contamination source are the same. Such an area is the Western Lagoon and the two sea waterways that connect the two canals. It is important to mention that the two results for 2020 from the two satellites (Landsat 8 and Sentinel-2) are different, and the reason for that might be that the C2RCC algorithm is not as well adapted for the Landsat 8 data as it is for Sentinel-2 (SNAP Forum). Consequently, for the Landsat 8 data, the algorithm was unable to produce results only for the water bodies because it cannot distinguish between land and water. For this reason, it was crucial to remove the data that were not valid by applying a mask.

**Chlorophyll-a**

Among the water quality parameter that TSM provides is chlorophyll-a, which is also shown in the maps concentrated in the Western Lagoon connected with the lake through one inlet on the western side during the different periods. Also, the chlorophyll-a concentration rate in NSC is more or less contaminant with that of the OSC and the central part of the lake. The results of the detection and distribution of chlorophyll-a were also produced from the C2RCC algorithm from both Sentinel-2 and Landsat 8, as shown in Figs. 10 and 11 and 12 and 13, respectively.

**Sentinel-2 Images** The concentration rate increased gradually towards the interior of the marine navigation pass of both OSC and NSC, which reached its maxima in some isolated pools in the connection of the NSC in its western boundaries. For the August Sentinel-2 data, the lowest values of all the years for the chlorophyll-a concentration are evident during August 2015, with the lowest values between 2 and 11 g m\(^{-3}\). The chlorophyll-a rate increased through the following years, with the highest values in August 2016 and 2018, with the highest values around 20 and 40 g m\(^{-3}\). It is essential to mention that a slight decrease in the overall chlorophyll-a concentration is evident during 2017, with a slight increase in the northern part of both canals where the values are around 4 to 14 g m\(^{-3}\). The decrease in rates continues in 2019 and 2020, and it is evident along the marine navigation pass of both NSC and OSC as well as in the central part of the Timsha Lake (Fig. 10).

The Sentinel-2 show that during 2019 the maximum values are around 10 to 23 g m\(^{-3}\), while during 2017, the chlorophyll-a values range between 5 and 14 g m\(^{-3}\). Those values are the same for both seasons and are concentrated in the northern part near the inlet and/or in the centre of the lake. The lowest values were observed during 2016, ranging from 2 g m\(^{-3}\) to a maximum of 14 g m\(^{-3}\) and during 2018, the rates ranged from 5 to 12 g m\(^{-3}\) in the whole area of interest (Fig. 11).

**Landsat-8 Images** The chlorophyll-a distribution produced from the C2RCC algorithm for the Landsat 8 is presented in Figs. 12 and 13.

From Fig. 12, the chlorophyll-a concentration for 2014 is significantly higher than the concentration for 2020. For 2014 during the dry season, the values range from 6 to 40 g m\(^{-3}\), while for 2020 are from 2 to 24 g m\(^{-3}\). The results for August of 2020 are pretty different from those from Sentinel-2 from the corresponding season. Based on Fig. 13, which is for the wet season, the values for 2014 and 2015 are the same and range from 24 to 40 g m\(^{-3}\). Chlorophyll appears to have the highest values in the New
Fig. 10 The chlorophyll-a concentration after the C2RCC algorithm that was used for the processing of the Sentinel-2 data during the month of August for the years 2015–2020.
Fig. 11  The chlorophyll-a concentration after the C2RCC algorithm that was used for the processing of the Sentinel-2 data during the months January–February for the years 2016–2020.
Canal and the central part of Lake Timsah for both seasons. It is important to mention that the two results for 2020 from Landsat 8 and Sentinel-2 are different; it might be that the C2RCC algorithm is not as well adapted for the Landsat 8 data as it is for Sentinel-2.

The profile graphs show the change in the values of TSM and chlorophyll-a for the dry season along the section, which is about 3100 m long (Fig. 14). Due to this fact and the fact that the satellite data have a high spatial resolution, it could result to an overloaded and unreadable graph. For this reason, they were resampled at 150 m for each year in order to obtain readable and less complicated graphs. The profile has shown that the highest measurements in both TSM and chlorophyll-a concentration are gathering at the western part of the line (representing the western part of the Timsah Lake). According to the graph, the higher TSM values are during 2020 and the lower in 2019. For the chlorophyll concentration, the highest measurements are in 2017 and the lowest in 2019.
Aquatic Reflectance

In this case, the second band 2-blue has been used. During the dry season for 2014, the Rrs is about 0 and 3324 sr\(^{-1}\). In 2020 for the dry season, the water-leaving radiance ranges from 0 to 1773 sr\(^{-1}\) (Fig. 15). Many things could have caused the difference between the rates in 2014 and 2020, which does not contain the entire area of interest (Oral Communication with USGS). And parameters like atmospheric disturbances, weather conditions, the time of day, and the sun angle are observed.

Discussion

This study aims to detect water quality changes in terms of TSM and chlorophyll-a of Timsah Lake, Ismailia (Egypt), using the two approaches of remote sensing techniques in detecting and monitoring water quality; semi-analytical and empirical modelling during the period between 2014 and 2020 in dry and wet seasons and also taking into consideration the changes that occurred during this period, like the construction of the NSC. Partially, we have obtained the above goal, and the main problem was the

Fig. 14 Profile graphs for TSM and chlorophyll-a concentration during the month of August for the years 2015–2020

Fig. 15 Aquatic reflectance band 2-Blue band image during August 2014 and 2020 Table 1 Landsat 8 and Sentinel 2 scenes used
inability of the C2RCC to be applied on Landsat 8 data, as well as the lack of archived Sentinel-2 images and insufficiency of ground truth data for validation.

The contaminants of aquatic and wetland environments are a common situation due to the changes in the surrounding area last years.

As it is confirmed by El-Serehy et al., (2018) and Abd El-Azim et al., (2018), there are three significant sources responsible for water quality changes in Timsah Lake (area of interest) such as agricultural drainage, anthropogenic activities, untreated domestic and industrial waste discharges. The results of the present work give some evidence of the water quality of the Timsah Lake in the period (2014–2020) by applying different methods to the optical satellite data. For this reason, PCA analysis was applied to obtain changes during the study period. TSM and chlorophyll-a concentration were gathered from satellite data by applying the C2RCC algorithm and aquatic reflectance.

It is vital to mention that the present study is carried out through August and January or February of the different years from 2014 to 2020; this is done to monitor the temporal changes during the 7 years. August is selected due to the fact that there is an increase in human activities concerning marine navigation, tourism, and fishing in Timsah Lake during the summer months. Also, the months January or February were selected to detect changes in the water quality of the area of interest, the wet season for the years 2014–2020. The chosen months for the dry and the wet season of the period of study were selected to examine seasonal variations, which is considered a good chance to correlate between the different human activities and water quality parameters. However, the application of the effect of month’s variability on water quality will be utilised effectively in case of shorter or longer temporal periods.

According to Sentinel 2 results, the lowest values of both TSM and chlorophyll-a are attributed to August 2015 for the dry season and 2016 for the wet season. This may be attributed to the cleaning up of the water bodies from solid wastes, algae, and suspended substances to prepare for the opening of the New Suez Canal on the 6th of August 2015. This also means that the Sentinel-2 acquisition was through a short time after the opening of the NSC, which interprets the low rates of TSM and chlorophyll-a concentration during this period. Consequently, the same results are achieved from the first acquisition of Landsat-8 (22-8-2014), i.e. after 2 weeks from the starting of the NSC digging, which is associated with the start of cleaning up the surface water of the OSC and associated water bodies which affects the reduction of TMS and chlorophyll-a concentrations in Timsah Lake. On the contrary, only one year after the opening of the NSC (in August 2016), the rates of TSM and chlorophyll-a concentration started to be raised, which may be due to the increase in marine navigation rates after the opening of the NSC. The rates continued rising in the following years, with a slight decrease in 2017, and the maximum rate was recorded in 2018. Also, the Western Lagoon is characterised by higher rates of TSM and chlorophyll-a during different periods. This trend may be due to several reasons attributed to the outfall of domestic and industrial wastewater that agreed with previous studies (El-Azim et al., 2018).

According to Landsat-8 results, the TSM and chlorophyll-a in August 2014 are lower than in August 2020 for the dry season, where higher values are attributed mainly to the Western Lagoon and the inlet of the Timsah Lake. For the wet season, both 2014 and 2015 show an extreme increase in chlorophyll-a and a minor concentration in TSM. Despite disagreement between the obtained results between Landsat-8 and Sentinel-2 satellite data for the year 2020, they are more or less common in the higher rates of TSM and chlorophyll-a in some parts of the Western Lagoon. Furthermore, as far as the C2RCC algorithm is concerned for the Landsat 8 results, as was mentioned before, these products are not as well presented because the C2RCC is not as well adapted for the Landsat 8 data as it is for Sentinel-2. As a result, the C2RCC results produced from the Landsat 8 data considered the whole area and were processed as one. Therefore, this data’s reliability is affected by many introduced errors that might be present even after the exclusion of the not meaningful processed data. As far as the methodology is concerned, it is building on the existing evidence of the studies of Filipponi (2018), Soomets et al. (2020) and Ogashawara et al. (2020) that have implemented their research and provided results that confirm the present study.

Aquatic reflectance provisional products provided the information that in 2020 the Rrs was smaller than in 2014. As a result, evaluating these products is necessary, especially in eutrophic and high turbidity waters, which are affected by many environmental and atmospheric conditions.

In line with the primary goal, the recorded rates of the TSM have shown that in the years 2014–2020, the connection of the Timsah Lake with the Western Lagoon and the Abu Attwa drain seems to be the sources that degrade the quality of the lake’s water. This might reveal that Lake Timsah is a high eutrophic lake, as was also pointed out by Mehana et al. (2016). In contradiction with the original hypothesis of this research, which presumed that the primary source of pollution was the NSC, new information that emerged revealed that the Western Lagoon and the streams mentioned before are considered a contamination starting point.

These tremendous amounts of wastewater discharging to the lake acquire different water types and pollutants from untreated sewage effluent and domestic or industrial
wastes, negatively affecting lake water. Also, marine navigation activities can contribute to the pollution through marine navigation pass in both OSC, NSC, and Timsah Lake by the presence of oil spills, human pathogens, and toxins, resulting in health series for human and marine life. The TSM, composed of many toxic tiny particles, is taken up within a few days by plankton and benthos animals causing harmful effects.

Of the harmful effects of the different types of pollutants received by the Western Lagoon (the source point of pollution in Timsah Lake), the decision-makers planned to close the Mahsama drain, which is the major source of pollutants to Timsah Lake, and they directed the treated water from the drain to be used for reclamation of thousands of acres in Sinai for agriculture. The Mahsama Sewage Treatment Station (MSTS) has been opened for operation in 2021; consequently, it is to be expected that the rates of pollutants in the lake will decrease in the forthcoming years.

It is recommended for this study, in the future, to be supported by in situ data for validation and in addition to applying continuous monitoring for all months of the years 2014–2020 to examine further the variation of TSM and chlorophyll-a concentration in order to assess and obtain robust results about the environmental status of the Timsah Lake.

Conclusions

The obtained results show that the rates of TSM and chlorophyll-a concentration do not exhibit a significant variability through the research period, where the rates range from moderate to high for both parameters except during the period of NSC construction and operation (2014–2015), which records low rates due to the operations of cleaning up the Canal and associated water bodies as a part for the preparation of NSC for marine navigation. However, it is still for the Western Lagoon and associated drains to be the main areas with higher TSM and chlorophyll-a concentration and, therefore, the main sources of diffusion of these indicators in the Timsah Lake.

As it was explained in the Discussion section, the source of degradation of the lake’s water quality seems to be the connection of the Timsah Lake with the Western Lagoon and the Abu Atwa Drain, where the recorded concentration of the TSM and chlorophyll-a exhibits higher values than the rest of the water surface in the years 2014–2020. Also, it is observed that the rate of TSM concentration in NSC is more or less compatible with that of OSC and the central part of Timsah Lake.

As mentioned before, TSM and chlorophyll-a results from Sentinel-2 data indicate that during the dry season, August 2015, there are lower values of TSM and chlorophyll-a, with a range between 4 and 17 g m$^{-3}$ and 2 and 11 g m$^{-3}$, respectively. However, the higher values of the TSM and chlorophyll-a concentration appear during August 2018 for the TSM, around 23 and 50 g m$^{-3}$ and for chlorophyll-a during August 2016 and 2018, around 20 and 40 g m$^{-3}$. These values are at their peak, especially during August 2018, 2019, and 2020. Specifically, high levels of TSM are evident and concentrated in the Western Lagoon.

Regarding the Landsat-8 results, the TSM for the dry period in August 2014 is lower than in the following years until 2020, where higher values are attributed mainly to the Western Lagoon and the inlet of the Timsah Lake. For chlorophyll-a, the highest value is recorded in 2014 than in any other year, concentrated in NSC and the Western Lagoon.

The Sentinel-2 data for the wet season (January–February) through the period 2016–2020, the lowest values are recorded during 2016, with TSM being around 3 to 10 g m$^{-3}$, while the maximum of the TSM concentration is visible during 2019 with values from 13 to 29 g m$^{-3}$ in most of the Lake Timsah.

The algorithm results for Landsat 8 data regarding the wet season (January–February) show that the changes between 2014 and 2015 are negligible, and the values range between 0.01 and 5 g m$^{-3}$.

To conclude, it is essential to emphasise that through the study period, the Western Lagoon connected with Timsah Lake through one inlet on the western side always recorded higher levels of TSM and chlorophyll-a, except at the time of the NSC opening (August 2015) which records the lowest rates of TSM and chlorophyll-a.

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Declarations

Conflict of interest The authors declared that they have no conflict of interest.

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