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RESEARCH ARTICLE

Using Multi-spectral Satellite Data for Mapping Bathymetry of Bitter Lakes, Suez Canal

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Abstract

The Suez Canal runs through an important water body, the Bitter Lakes which are deepened regularly to suit passing by or parking vessels of different drafts. The bottom topographic is dynamically changing due to sedimentation by ships and water current movements that are usually impacting and requiring those continuing dredging processes performed by the Suez Canal Authority. Basically, studying the bottom dwellers of any lake requires bathymetric data which is very costly. Therefore, bathymetry maps can be derived from passive optical satellite sensors (multispectral). The present study used Landsat-8 and Sentinel-2 satellite imagery to produce water depth of the Bitter Lakes, Suez Canal. The satellite image data was preprocessed then using log ratio to extract the raster values which were integrated with i*n situ* measured depth data to estimate absolute water depths. The Landsat-8 resulted in depth was supportive to detect bottom topographic, using two different datasets, one by using coastal, green, and red bands with R squared of 0.89 and the other dataset by using blue, green, and red bands with R squared of 0.84. Comparing with the Sentinel-2 resulted in depth revealed R squared of 0.81 by using a dataset of blue, green, and red bands for pixel size 10 m. The study could be used for further monitoring of lake bathymetry in a continuous way and detecting sedimentation dynamics.

Keywords: Bitter lakes, Bottom topography, Multispectral imagery, The Suez canal

1. Introduction

The Bitter lakes represent the biggest water volume of the Suez Canal. They are divided into Great and Little Bitter Lakes that are connected to each other, occupying an elongated and shallow basin. They have a significant socio-economic value achieved through various activities along its shoreline i.e. tourism villages, fishing landing sites, agricultural lands and the power plants (Abu-Sultan power plant). Fishing activity in the Great Bitter Lake depends mainly on three landing sites; El-Deversoir, Faied, and Fanara. Despite the high diversity of fishes and invertebrates in the lakes, the available studies have only focused on commercial fishes and different fishing techniques usually used around the lake (Mohammed, 2009). Hence, there is no available data describing the biodiversity in the Bitter Lakes.

The subsurface sediment of the shallow parts bordering the lakes is mainly loose and composed of sand and mud (Stanley et al., 1982). However, the central part of the Great Lake is characterized by the presence of evaporites; Halite and Gypsum, with subsequent clastic admixtures (El-Masry, 1992). The bitter lakes form a natural salinity barrier along with the Suez Canal (Por, 1978). According to the historical data, the salinity of the Bitter Lakes varied from 62 % in 1869 (Sears and Merriman, 1980) to 41 % in 2009 (Mohammed, 2009). This gradual

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decrease of bottom salts (evaporites) is attributed to the sedimentation deposits and deepening process of the Suez Canal allowing the lessepsian migration; which is the transport of different aquatic species from various taxonomic groups from the Red Sea to the Mediterranean Sea and vice versa since the Suez Canal was opened in 1869 (Por, 1971). The bottom of the Bitter Lakes is covered by seagrasses beds and seaweeds. Seagrasses usually occur in mud or fine silty bottoms. El-Manawy (1992) has reported a total of 97 species of green, brown, and red algae, where they mostly thrive in shallow waters. This distribution is probably due to the increased turbidity in greater depths prohibiting sun light and thus proper algal growth.

The bathymetry maps, which determine the topography of the seafloor are considered a key tool in various marine studies. As it provides basic data used in different approaches; hydrology, fisheries assessment, habitat mapping, seafloor profile and sedimentation, in addition to, generating navigation charts (Mohammed, 2018). Moreover, they are used to monitor the movement of sediments to produce the hydrographic charts for safe navigation (Botha et al., 2016). The bathymetry mapping used to be measured by acoustic instruments only, which faced several difficulties in shallow waters as it is limited to where vessel can navigate, moreover, it is time and money consuming (Hernandez and Armstrong, 2016).

Remote sensing can be considered as one of the most promising tools to map ocean basins, because of its wide coverage related to the area. Active sensors like airborne laser bathymetric and light detection and ranging (Lidar) can effectively determine the depth of shallow and clear water, but it is considerably expensive (Goodman et al., 2013; Knudby et al., 2014; Leiper et al., 2014). On the other hand, data obtained from passive optical satellite sensors (multispectral and hyperspectral) provide applied means for regularly mapping and monitoring bathymetry (Lyzenga, 1978; Brando and Dekker, 2003; Jagalingam et al., 2015).

Through the past decade, many remote-sensing platforms have produced bathymetry maps using satellite sensors of moderate spatial resolution. There are remote sensing satellites that offer imageries with high spatial and spectral resolution; however, they are not affordable. While, Landsat-8 imagery (spatial resolution of 30 m) are open source (U.S. Geological Survey (USGS) website) accessible for researchers which have employed the data in various applications. In addition, its temporal resolution is vital in monitoring environmental studies. Furthermore, they are also used to retrieve information about coastal environments; coastal optical water properties; benthic habitat composition; bathymetry and sedimentations (Botha et al., 2013; Jupiter et al., 2013).

Many methods and different algorithms were used to retrieve water depth from remote sensing data (Gholamalifard et al., 2013; Zoffoli et al., 2014). The first used algorithms were the simplest and easiest to apply as a band ratio (Lyzenga, 1978; Stumpf et al., 2003; Mishra et al., 2007). Type of bottom cover is known to affect the reflected image; for instance, dense sea grass beds could give the impression of deeper waters while sandy bottoms reflect the right depth under suitable atmospheric conditions (Stumpf et al., 2003). To avoid this ambiguity, the used method depends on Philpot (1989), who mentioned that the difference in depths can give more prominent result than the bottom itself.

The present study discusses the ability of bathymetry mapping for Bitter Lakes using remote sensing techniques depending on the integration between different datasets. As, there is no available data for the bathymetry of the Bitter Lakes, the present study aims to establish bathymetric map as a base map for future environmental studies. In addition, the study differentiates between both Landsat-8 and Sentinel-2 satellites for most accurate bathymetry mapping of small waterbodies.

2. Materials and methods

2.1. Study area

The Bitter Lakes are located between 99.870 km at El-Deversoir and 130.580 km at Gineifa according to the kilometric scale of the Suez Canal and covers an area of about 232 km^2. The study area is bounded by latitudes 30°: 10′ - 30°: 26′ N, and longitudes 32°: 10′ - 32°: 40′ E. The Bitter Lakes are signified as Great Bitter Lakes and Little Bitter Lakes connected to each other as shown in (Fig. 1). All Great Bitter Lakes and half of Little Bitter Lakes belong to Ismailia governorate whereas, the other half of the Little Bitter Lakes belong to the Suez governorate.

2.2. Data collection

The present study depends on the integration between different datasets (Fig. 2); field depth measurements, navigational maps and two types of satellite imagery.

(1) A visual survey was carried out for the western part of the great bitter lake's bottom to recognize the benthic habitat distribution. The acquisition

Fig. 1. Location map of Bitter Lakes.

of depth points was determined in March, 2021 using single beam echo-sounder instrument.

(2) The depths of passageway and ships waiting areas were collected using navigational map of Suez Canal (United Kingdom survey, bathymetric map, 1999).

(3) Landsat-8 satellite imagery with pixel resolution of 30 m was acquired on the 3rd of April 2021.

(4) Sentinel-2 imagery with pixel resolution of 10 m, acquired on the third of April 2021

2.2.1. Landsat-8 satellite image

Landsat-8 was launched in 2013, and it has an Operational Land Imager (OLI) provides high quality multispectral images at the resolution of 30 m (15 m for panchromatic) and a revisiting time of 16 days. This satellite is providing data continuously to the Landsat Earth observation program, which started in the 1970s. The Landsat-8 OLI is collecting data using nine spectral bands in different wavelengths. These wavelengths are visible, near-infrared, shortwave in eight spectral bands, and TIRS bands 10–11 which collected at 100 m but resampled to 30 m. The raw data for the study area was free-downloaded from USGS online site (URL: earthexplorer.usgs.gov).

2.2.2. Sentinel-2 satellite image

The Sentinel-2 mission was equipped with identical Multispectral Instruments (MSI) capable of acquiring data in 13 bands: 4 visible bands, 6 Near-Infrared bands, and 3 Short-Wave Infrared bands. The spatial resolutions of bands are different between 10 m, 20 and 60 m. The revisiting time is 10 days at the equator with 1 satellite, and 5 days with 2 satellites (S2A and S2B). The data of the study area was free-downloaded from USGS online site (URL: scihub.copernicus.eu). However, the Level-1C product provides ortho-rectified top of atmosphere reflectance with a sub-pixel multi-spectral and multi-date registration. The satellite image used (S2A) four bands (blue, green, red, and Near-infrared (NIR)) of pixel size 10 m was used.

2.3. Data processing

Flow chart show the framework of processing methods at (Fig. 3).

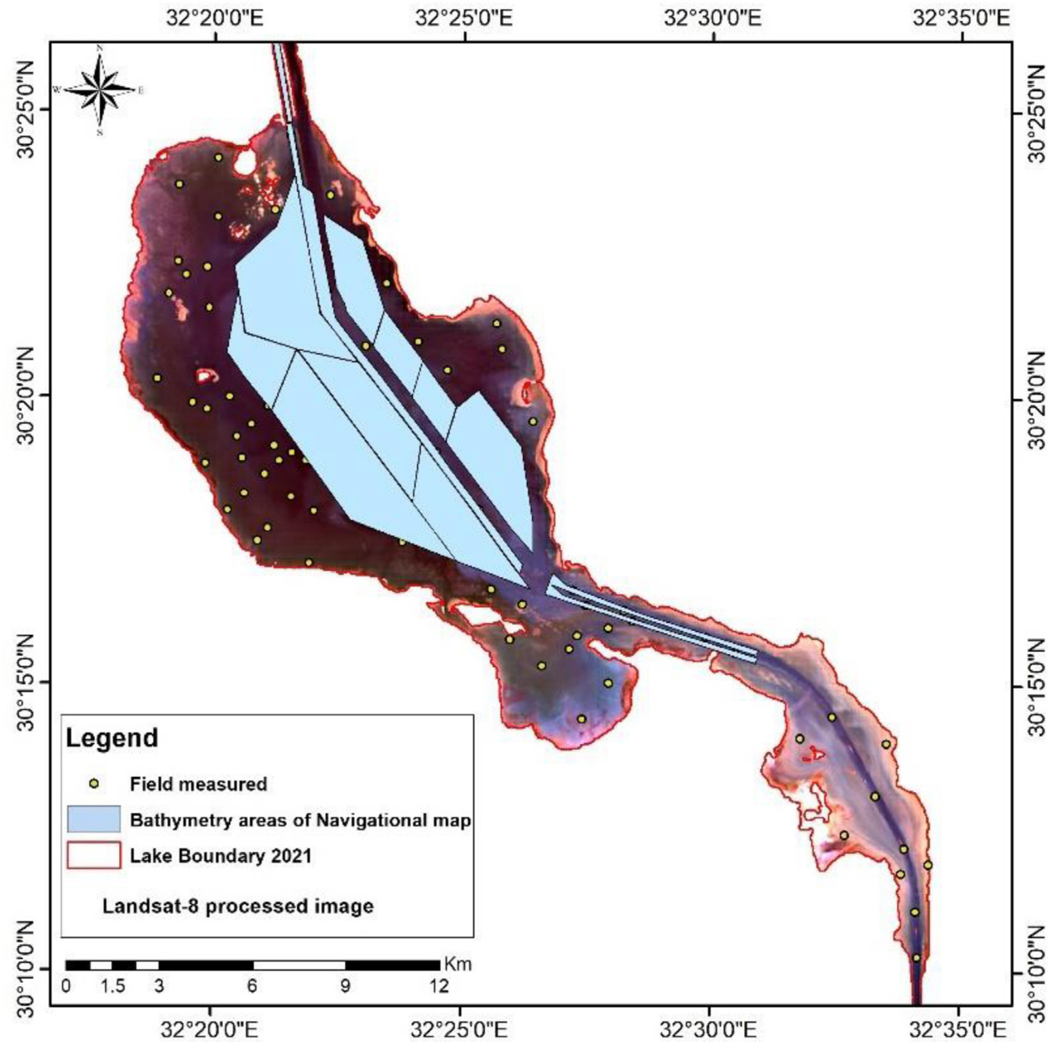

Fig. 2. Show the points in yellow color is in situ measured depth and the areas of blue is the depth readings taken from navigational map.

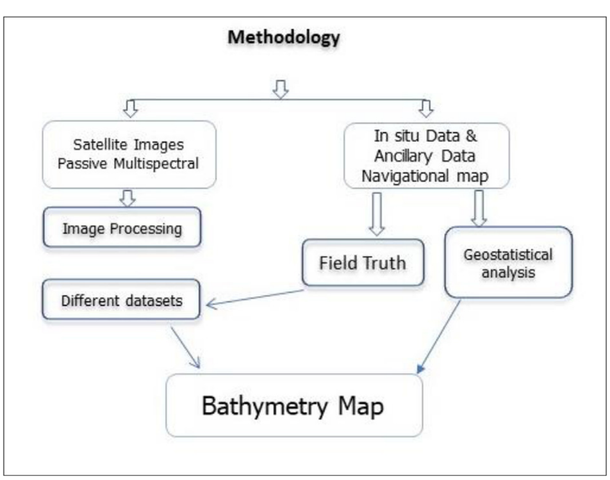

Fig. 3. Show the flow chart for methodology.

2.3.1. Geostatistical analyses

The measurements of *in situ* depth was analyzed and modeled in framework of data transformation to create continuous information raster of bathymetry. The dataset was interpolated with the values extracted from navigational map to fill the gap of center of the lake and generate a bathymetry map (base map). Where, the model estimates raster surface values for each pixel using the value and distance of nearby points.

2.3.2. Remote sensed data analysis

The satellite image underwent preprocessing to correct the atmospheric effects. This was achieved using radiometric calibration and Fast Line-of-sight Atmospheric Analysis of spectral Hypercubes

(FLAASH) module, which is a developed module in Envi-5 program for atmospheric correction.

The two dataset of band combination (blue, green, red, and NIR) and (coastal, green, red, and NIR) was used to generate relative depth raster. It was processed using Ratio Transform Algorithm according to (Stumpf et al., 2003):

$$Z = m_1 \frac{\mathrm{In}(R_w(\lambda_i))}{\mathrm{In}(R_w(\lambda_j))} - m_0$$

Where Z is depth, m1 and m0 are the offset and gain determined empirically, R_w is observed radiance of bands, λ_i refer to blue band and λ_j refers to green band.

The calibration was done to the resulted relative water depth raster to absolute depth using the ground truth from base map values in a linear regression. Linear regression is a simple method for constructing predictive model when there are two highly correlated variables (*in situ* data vs. satellite data). Linear regression bathymetric model was developed in its simplest form, a linear model specifies the relationship between a dependent (response) variable *Y*, and a predictor variable, *X*:

$$Y = mX + b \quad (1)$$

Where, b is the intercept and *m* is the Slope.

3. Results and discussion

3.1. Interpolation map

The visual survey of the benthic habitat showed sandy bottom from the shoreline and muddy bottom appeared towards the center of the lake. Seagrass beds and seaweeds were distributed in the western part of the great bitter lakes (Fig. 4). Small patches of rocky shoreline along the western part were covered by seaweeds (Fig. 5). The turbidity movement were represented in the center of the lake by Satellite image (Fig. 6).

Fig. 4. Shows distribution of seagrasses beds with turbidity effect.

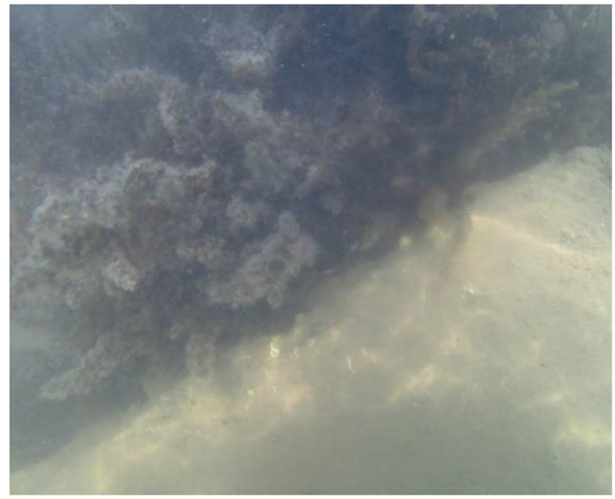

Fig. 5. Shows seaweeds cover on shallow shoreline.

According to the compiled bathymetric map of the interpolated depth datasets of *in situ* and navigational map (Fig. 7) it can be observed that; the lake margins exhibit gentle slope from the shore line towards the Suez Canal navigation channel. The minimum recorded values of the shallow area ranged from 0 to 0.85 m. And expectedly, the maximum value was recorded at the navigation channel (19 m).

3.2. Bathymetry map from satellite images

The relative depth after satellite imagery has shown strong linear relationship with the *in-situ*

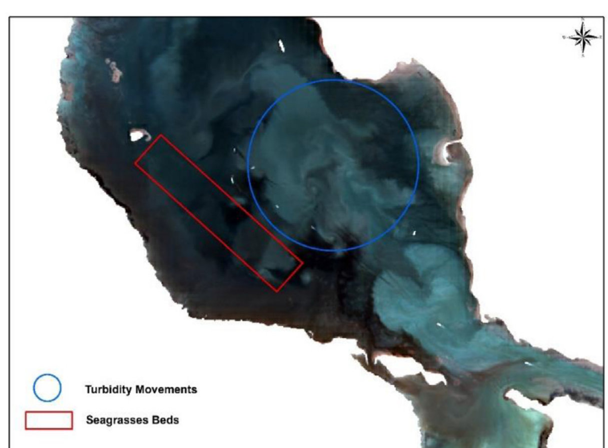

Fig. 6. Satellite image (RGB (RED, GREEN, and BLUE, mixing color)) shows turbidity movements and distribution of seagrasses beds.

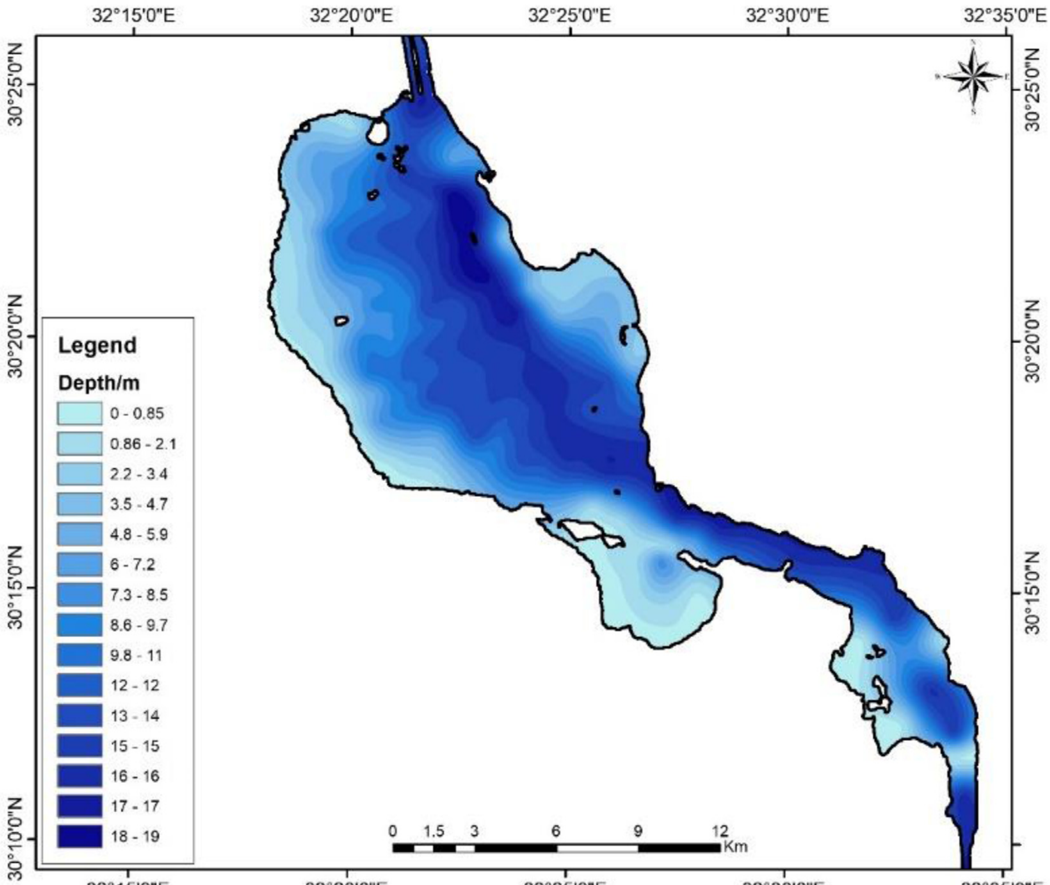

Fig. 7. Bathymetric map after interpolated data of in situ and navigational map.

depth (Figs. 8 and 9). The absolute depth calibration showed linear correlation with R2 equal to 0.84 after using dataset of (blue, green, red, and NIR bands). Furthermore, the integrational datasets of ground truth depth and satellite data results in a depth range value of 0–14 m (Fig. 10). And recorded R2 equal to 0.89 by calibrated absolute depth for dataset of (coastal, green, red and NIR bands) as shown

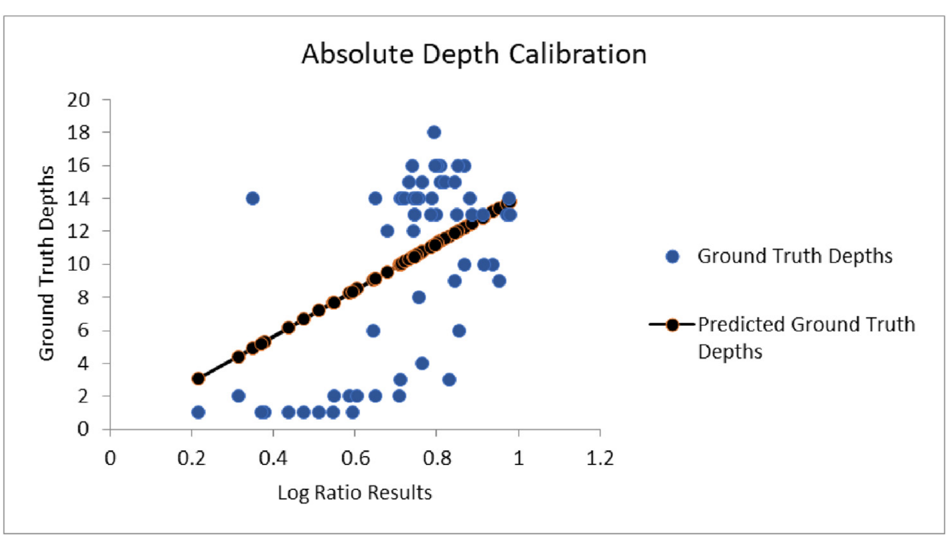

Fig. 8. Show chart of linear regression using Landsat-8 (blue band).

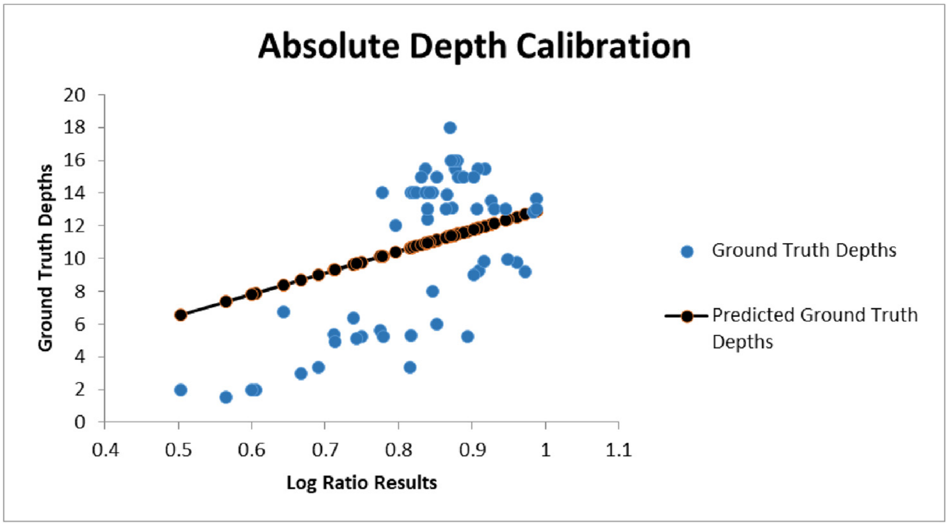

Fig. 9. Show chart of linear regression using Landsat-8 (coastal band).

on (Fig. 11) with depth range from 0 to 13 m. The Sentinel-2 relative depth (Figs. 12 and 13) revealed from using dataset of (blue, green, red, and NIR bands) in addition to advantage of a pixel size of 10 m, confirm R squared with 0.81.

The present study revealed that this method is promising for detecting depth on clear water, where bathymetry algorithm was much more sensitive to changes in bottom depth than bottom composition (Dierssen et al., 2003). While in comparison, Landsat-8 was more accurate and sensitive to shallow areas than Sentinel-2 that, despite its high resolution, it did not show depths lower than 2 m (Fig. 13), probably due to the lacking a coastal band, which is a drawback that was mentioned in a previous study (Mohammed, 2018). On the other hand, Landsat-8

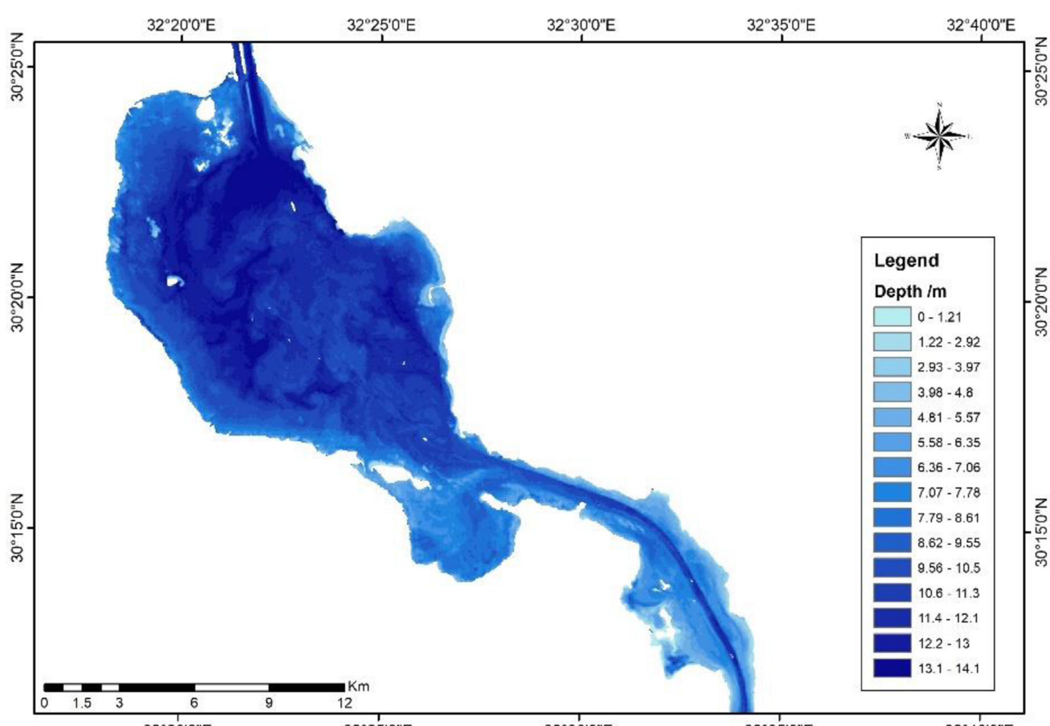

Fig. 10. Bathymetric map after integrated Landsat-8 satellite image with depth datasets using blue band.

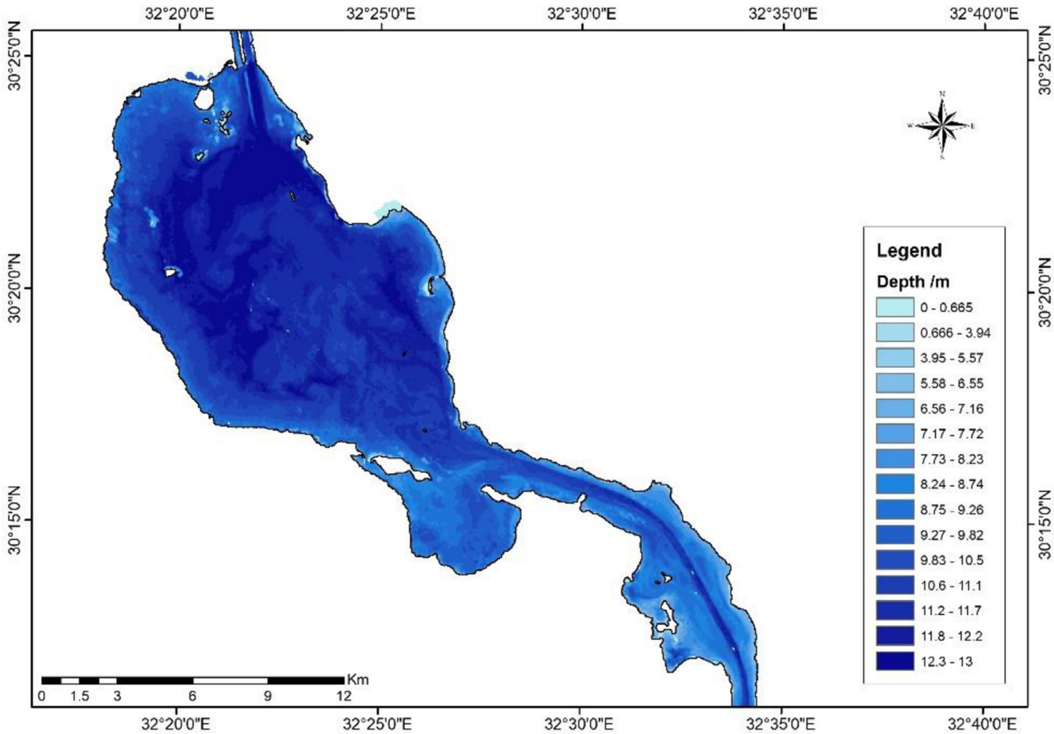

Fig. 11. Bathymetric map after integrated Landsat-8 satellite image with depth datasets using Coastal band.

images have shown more sensible variation of depths starting from 0 m depth as predictable and known on ground.

So according to Landsat-8 (Figs. 9 and 11); the lake bathymetry could be classified into three zones; the shallow water, the waiting areas for ships and the two ways of navigation channel. The first zone starts from the shoreline (0 m) to depths reach up to 2 m in the western and eastern parts of the lake. This shallow water is important for juvenile fishes, acting as shelter and feeding areas (Ahmed et al., 2004; Mohammed, 2009; Ahmed and El-karamany, 2013). It is also suitable for tourism activities extending along the western bank of the lakes. The second zone which is the waiting areas for ships, has bathymetry ranges from 13 m to 14 m. This area

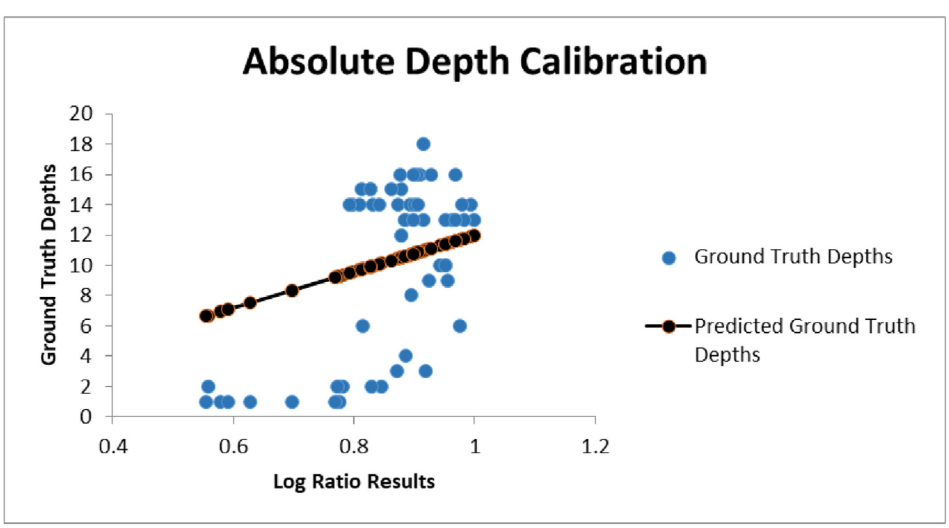

Fig. 12. Show chart of linear regression using Sentinel-2 (blue band).

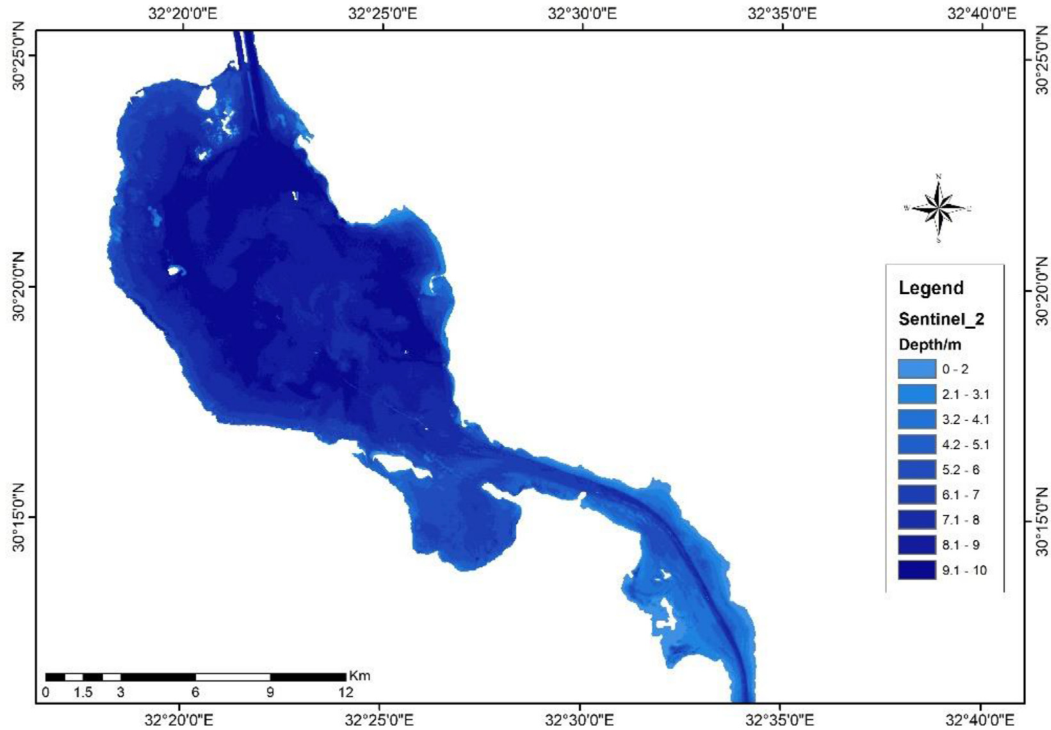

Fig. 13. Bathymetric map after integrated satellite image with depth datasets using Sentinel-2 blue band.

undergoes deepening processes on regular basis to compensate with the draft of passing ships. As a result, this area has increased turbidity levels. The last zone which represents the two ways of navigation channel has a depth that varies between 18 m at El-Deversoir; 15.5 m at the lake center and 15 m at the connection between Great and Little Bitter Lakes.

Comparing the interpolated map of depth measurements and satellite extracted depth data; it was observed that the shallow areas in both eastern and western sides were nearly identical. However, the center of the lake varied on the satellite estimated maps according to (Liu et al., 2021; Duan et al., 2022) when the depth was deeper than 15 m, the bathymetry error increased. In addition to the turbidity related to the water movement, that clearly appeared on satellite imagery in agreement with (Kouadio et al., 2020).

The integration between *in situ* depth data with satellite image resulted in a map that presented the real status of the lake which enable a realistic monitoring of turbidity movements and sediments settling. In agree with Wu et al. (2021) the established method with different datasets appropriate for monitoring dredging activities, especially in areas with polluted water mud sedimentation. Furthermore, the satellite data categorized the bathymetry and the bottom cover through spectral reflectance related to benthic type of sand and seagrasses. The reason of the seagrass appearance in the imagery is that the green reflectance (555 nm) is not highly absorbed by most of the benthic vegetation, this was mentioned by Dekker et al. (2011) and Mustafa et al. (2019).

Therefore, it was valuable to detect the turbidity movement and seagrasses beds distribution after water column correction (Dekker et al., 2005; Dierssen et al., 2003). However, the satellite image derived false bathymetry due to water turbidity using linear regression in this study. On the other hand, Wei and Theuerkauf (2021) estimated high accuracy bathymetry to turbid water on using polynomial regression.

Environmental studies, giving indications on benthic biota distributed on the sea floor at different depths. Furthermore, since sedimentation is a major contributing factor that affects submerged marine plants, its crucial to figure out its rates both spatially and temporally.

4. Conclusion

Ecologically, the Bitter Lakes have a deficiency on bathymetric data. The main product from this study is a novel bathymetry map from remote sensed data, as well as, a functional description of different depth zones of the lake from very shallow to deep water at passage way. In addition to, water column status that was resulted from an integration between satellite images and field data, which is useful for studying biological aspects of bottom dwellers distribution. The remote sensing data was capable to identify the real state of the Bitter lakes including the dynamics of sedimentations movements and benthic biota distribution. We can confirm that, using satellite data to map benthic habitats especially seaweed and seagrass beds is more informative when eliminating the effect of turbidity. Finally, in waterbodies such as ponds and lakes, recommend using Landsat-8 satellite data in detecting the bathymetry of narrow shorelines especially using coastal band.

Consent for publication

No need for any ethical approvals or informed consent.

Availability of data and material

The data that support the findings of this study are available on request from the corresponding author.

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Author's contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by A. H. M., S. S. A.-H., H. S. I. and E. E. A.E. The first draft of the manuscript was written by A. H. M. and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Conflicts of interest

The authors have no relevant financial or non-financial interests to disclose.

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