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The Impact of Building a Causeway between the Al-Doha and Shuwaikh Areas in Kuwait Bay on Water Quality Using Remote Sensing and GIS

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Abstract

Since seawater is the main source of water in Kuwait, water quality must be monitored and observed continuously. Remote sensing is considered to be a very practical method for conducting such a study, especially in prohibited and non-accessible areas. The Al-Hishan area is a small bay located between Al-Doha and Shuwaikh in Kuwait Bay. Although it is a coastal area, many industrial activities have been constructed. Also, the construction of the Jaber Al-Ahmad Causeway has increased the accumulation of sediments and biomaterials in this area. Data were taken from 2013 until 2023 using Landsat imagery, which have been corrected and analyzed using the Google Earth Engine (GEE) platform with multiple indices such as "Total Suspended Solids (TSS), Turbidity, Secchi Disk Depth (SDD), Water Surface Temperature (WST), Suspended Particulate Matter (SPM), and Normalized Difference Water Index (NDWI)" to compare the changes in water quality in this area before, during, and after the construction of the Jaber Al-Ahmad Causeway. The results detected some changes in water quality in many factors, such as temperature and chlorophyll. Observing and monitoring water quality is very important and necessary, especially in countries with limited sources of water. The new techniques in remote sensing and Geographic Information Systems (GIS) have proved to be a very practical way to conduct such a study with high accuracy.

Keywords

Remote Sensing, Geographic Information System (GIS), Water Quality, Jaber Al-Ahmad Causeway, Google Earth Engine (GEE)

1. Introduction

Water is a fundamental element for all living organisms. Furthermore, it serves as the foundation for both industry and agriculture. Human food is obtained from agriculture, and since water is essential to all aspects of life, it must be conserved to protect life and the lives of future generations. Since seawater is the main source of consumable water in Kuwait, water quality must be monitored and observed continuously. Kuwait Bay is a shallow-depth, semi-enclosed waterbody in the northwestern part of the Arabian Gulf [1] (**Figure 1**). It is important to preserve the bay since it serves as a source of freshwater, sustenance, and tourism. **Figure 2** shows that all urban land use covers 2.9% of Kuwait's total area, and 2.5% of this area is close to the sea [2]. Also, this expansion near the sea can worsen pollution.

Marine ecosystems are affected by the expansion of the coastal population. Infrastructure will be compromised, increasing marine pollution. Coastal development will enhance activity, thereby increasing the volume of waste entering the water. Although traditional in-situ water quality monitoring methods are accurate, their spatial and temporal coverage is frequently restricted [3]. For example, the usage of remote sensing technology, readily available in the market, is an ideal solution to constantly check, monitor, and record water quality levels. Remote sensing technologies have become an important resource for obtaining useful data for environmental applications [4]. Within the context of water quality testing and water framework directives, the use of remote sensing technologies has always proved to be a crucial tool for obtaining data.

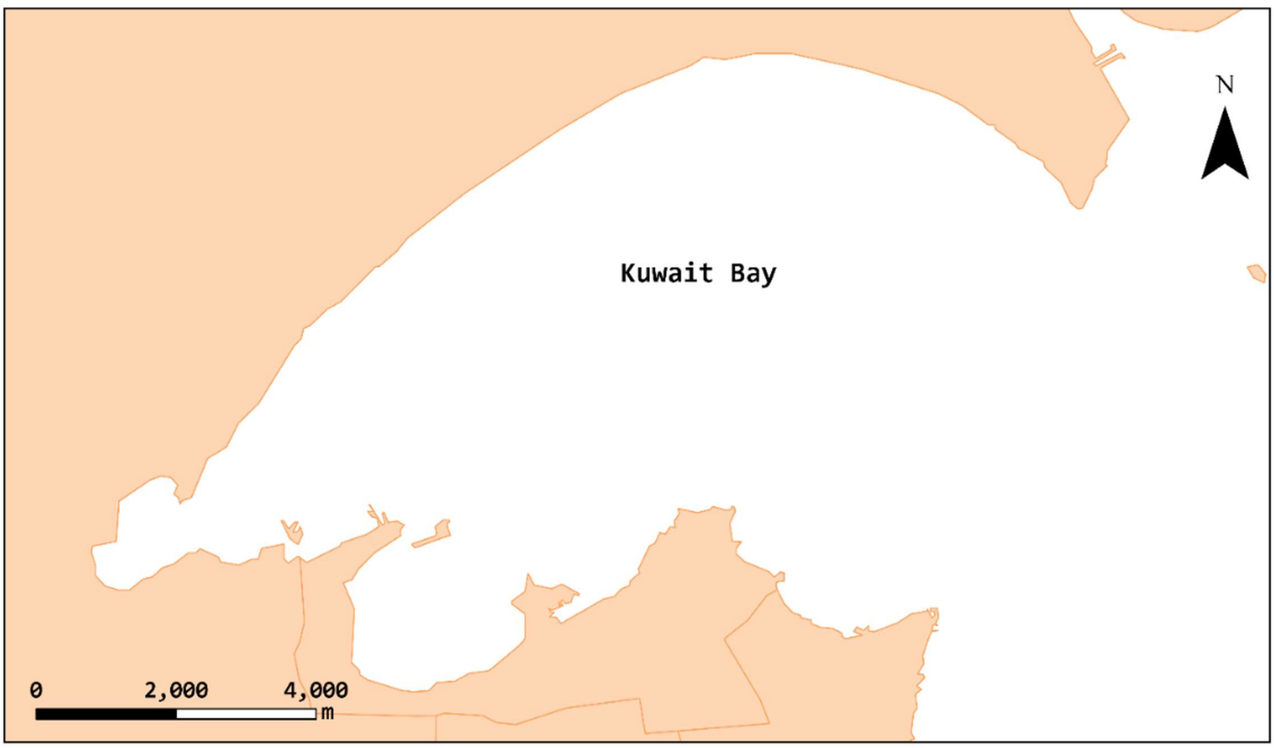

Figure 1. Kuwait Bay.

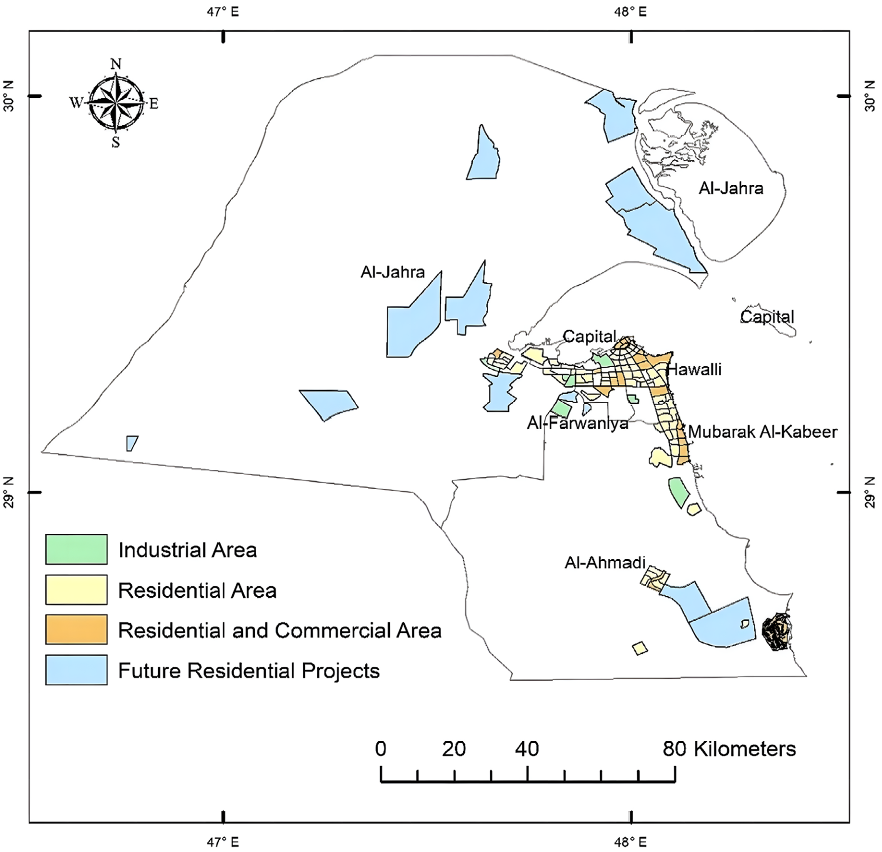

Figure 2. Urban land use in Kuwait [2].

Remote sensing techniques currently used to test water quality properties help in the identification and description of water characteristics (physical, chemical, thermal, and biological). However, it is crucial to mention that it is impractical to use a single water quality technique to support a fact or a case study. For example, when studying the parameters of water, we should consider the differences between water for human use and irrigation water. The usage of remote sensing techniques plays an effective and integral role in monitoring and assessing the quality of surface waters, and is crucial in the management and improvement of water quality. In situ collection of water samples for laboratory analyses to evaluate water quality is very important [5]. Therefore, the nature and scope of using remote sensing and Geographic Information System (GIS) have been clearly demonstrated in this project carried out at the Al-Doha causeway, in the State of Kuwait. According to Chen *et al.* (2004) [6] in their study, the role of remote sensing technology in the EU water framework directive (WFD), published in the Journal of Environmental Science & Policy, the usage of remote sensing of water quality and monitoring is better than traditional monitoring and measurements because it gives images with spatial and temporal data relating to water characteristics. The role of remote sensing technology is to provide global and local data for both present and past decades, which is archived in an accessible database [6]. Satellite imagery, associated with remote sensing technology, is another important merit. Satellite imagery, particularly from sensors like Landsat 8, provides valuable data for assessing water quality parameters such as chlorophyll a concentration, turbidity, SPM, and SST [7]. In addition, the usage of remote sensing technology for testing and determining water quality is also very cost-effective.

The usage of remote sensing technology offers a cost-effective and efficient means of monitoring water quality over large spatial scales and frequent temporal intervals [8]. It is because of these unique merits that remote sensing and Geographic Information System (GIS) technology were used in the case study—Al-Doha causeway in the State of Kuwait.

1.1. Statement of the Problem

The Sheikh Jaber Al-Ahmad Al-Sabah Causeway is one of the important projects in Kuwait that simplifies the connection between Kuwait City and northern Kuwait, reducing travel time and enhancing land development. It contains two connections: the Main Link and the Al-Doha Link [9]. These infrastructure projects can affect the environment, mostly in enclosed bays and small regions (**Figure 3**).

Figure 3. Location of Al-Doha causeway.

Construction activities, including dredging, land reclamation, and pile driving, may increase turbidity, sedimentation, and disturbance of benthic habitats [10]. These operations might have a detrimental effect on marine ecosystems and water quality.

This study aims to determine whether the Doha causeway can affect water quality by using remote sensing techniques and GIS.

1.2. Objectives

The study's main objectives are to evaluate water quality parameters (Chlorophyll-a, Turbidity, Water Surface Temperature (WST), and Total Suspended Solids (TSS)) in Kuwait Bay and examine the spatial distribution of these parameters in the area close to Al-Doha Causeway before, during, and after the construction phase.

1.3. Importance of the Study

This study shows how large-scale infrastructure can influence a delicate coastal ecosystem in Kuwait Bay. Combining satellite data with cloud computing provides a low-cost method for continuous environmental monitoring. The results will help Kuwaiti decision-makers and planners develop policies that support the preservation of maritime habitats. Furthermore, the methods used here could guide similar research elsewhere in the region or in areas facing similar environmental challenges.

2. Literature Review

According to Chen *et al.* (2004) [6], the use of remote sensing for water quality and monitoring is better than traditional monitoring and measurements because it provides both spatial and temporal data relating to water characteristics. The role of remote sensing technology provides the potential capacity for systematic observations at scales ranging from local to global and for the provision of data archives extending back over several decades [6].

Jerry *et al.* (2003) [5] discuss in more detail the role of remote sensing techniques to monitor and test water quality. Remote sensing technology helps in the identification of water characteristics related to the physical, chemical, thermal, and/or biological characteristics of water. They also stress that it is "difficult to use a single technique for all studies. For example, physical, chemical, and biological parameters of water that are suitable for human consumption are different from those of water suitable for irrigation. Most important of all, water quality is impacted by materials delivered to a water body from either point or nonpoint sources. Point sources refer to a single source, such as a pipe or a ditch, while a nonpoint source is related to the landscape and how it reacts with water movement, land use, and anthropogenic and natural activities on the water surface. Whether water quality is affected by either point or nonpoint sources, the usage of remote sensing techniques plays an effective and integral role in monitoring and assessing the quality of surface waters, and is crucial in the management and improvement of water quality. In situ measurements and collection of water samples for subsequent laboratory analyses employed to evaluate water quality are very important [5].

Howard *et al.* (2004) [11] discuss the growing relevance of real-time remote monitoring of water quality, with the use of sensors, telemetry, and computing technologies. The authors found that remote sensing techniques have high capabilities in monitoring and observing water quality. This, in turn, helps to better understand hydrologic properties at both temporal and spatial scales. Such developments have also helped to derive better statistical and mechanistic modeling to monitor water quality, whether at causeways, watersheds, freshwater, estuarine, or marine ecosystems. Real-time remote monitoring of water quality has also enhanced the observation of hydrologic variability, which can be an early warning system for harmful algal bloom events [11].

Xu *et al.* (2014) [12] discuss the growing usage and importance of wireless sensors, also called remote sensors, in effectively monitoring the marine environment. The need for the most effective marine technology has directly resulted from the need to address the challenges faced in the marine environment. To meet these challenges, many marine environment observation systems have been developed in the last decade. Most traditional marine observation systems, which employ an oceanographic research vessel, are not efficient because they are simply too expensive, time-consuming, and have lower resolution both in time and space. On the other hand, Wireless Sensor Networks (WSNs), also called remote sensors, are more efficient in monitoring water quality because they offer numerous benefits—they are unmanned, easy to deploy, provide real-time monitoring, and are also low cost [12].

Other studies also confirm that remote sensing is an effective way to study water quality indicators over large areas without in-field sampling by collecting digital data that can be easily read in computer processing. The traditional way is accurate, but it takes a long time and effort to collect the sample and conduct laboratory analysis, whereas remote sensing is a valuable tool for water quality assessment [13]. Multispectral data from sensors like Landsat, MODIS, and Sentinel-2 help estimate parameters such as chlorophyll a, turbidity, and SPM [14]. Specific algorithms designed for different water types improve accuracy. For example, the 3-band Ocean Color (OC3) algorithm works well for chlorophyll a in open ocean waters [15], but coastal waters need modified approaches [16].

Challenges in water quality remote sensing include correcting for atmospheric effects, sensor limitations, and varying water optical properties [17]. Improvements in sensor technology, algorithms, and data processing methods are making remote sensing applications more reliable for water monitoring [18].

According to Huang *et al.* (2020) [19], the construction of a causeway in Hangzhou Bay (China) has affected the SST and suspended sediment concentration (SSC) in the bay; this was monitored by applying an improved single-window algorithm to Landsat 8 imagery.

Also, Guo *et al.* (2020) [20] approved the accuracy of remote sensing in monitoring the total suspended solids in water bodies by comparing the results from digital data analysis with in situ data. The study applied a developed novel algorithm to Landsat-derived reflectance corrected for Rayleigh scattering in the Pearl River area. The study approved that the causeway decreases the amount of TSS in the surrounding area but increases it on the other side of the causeway.

Moreover, by using the Moderate Resolution Imaging Spectroradiometer (MODIS) product, Yuan *et al.* (2019) [21] evaluate coastal biogeochemical and physical processes and monitor water quality in Jiaozhou Bay in China to assess the impact of the cross-sea causeway on the water of the bay. The study focused on observing chlorophyll a concentration and total suspended sediment. The results showed that chlorophyll a values were higher at the causeway than in the area around it, and TSS values at Jiaozhou Bay Causeway were also higher in 2018. This means that the Jiaozhou Bay Causeway can affect water quality.

3. Study Area

Kuwait Bay is the primary focus of the research. This area is characterized by its oval shape, and the approximate area is 720 km^2 [22]. The geographical coordinates of this area range from 29.5˚N to 29.8˚N latitude and 47.7˚E to 48.1˚E longitude. Figure 4 shows the study area and highlights the Doha Link section of the Sheikh Jaber Al-Ahmad Al-Sabah Causeway and the defined study area boundaries.

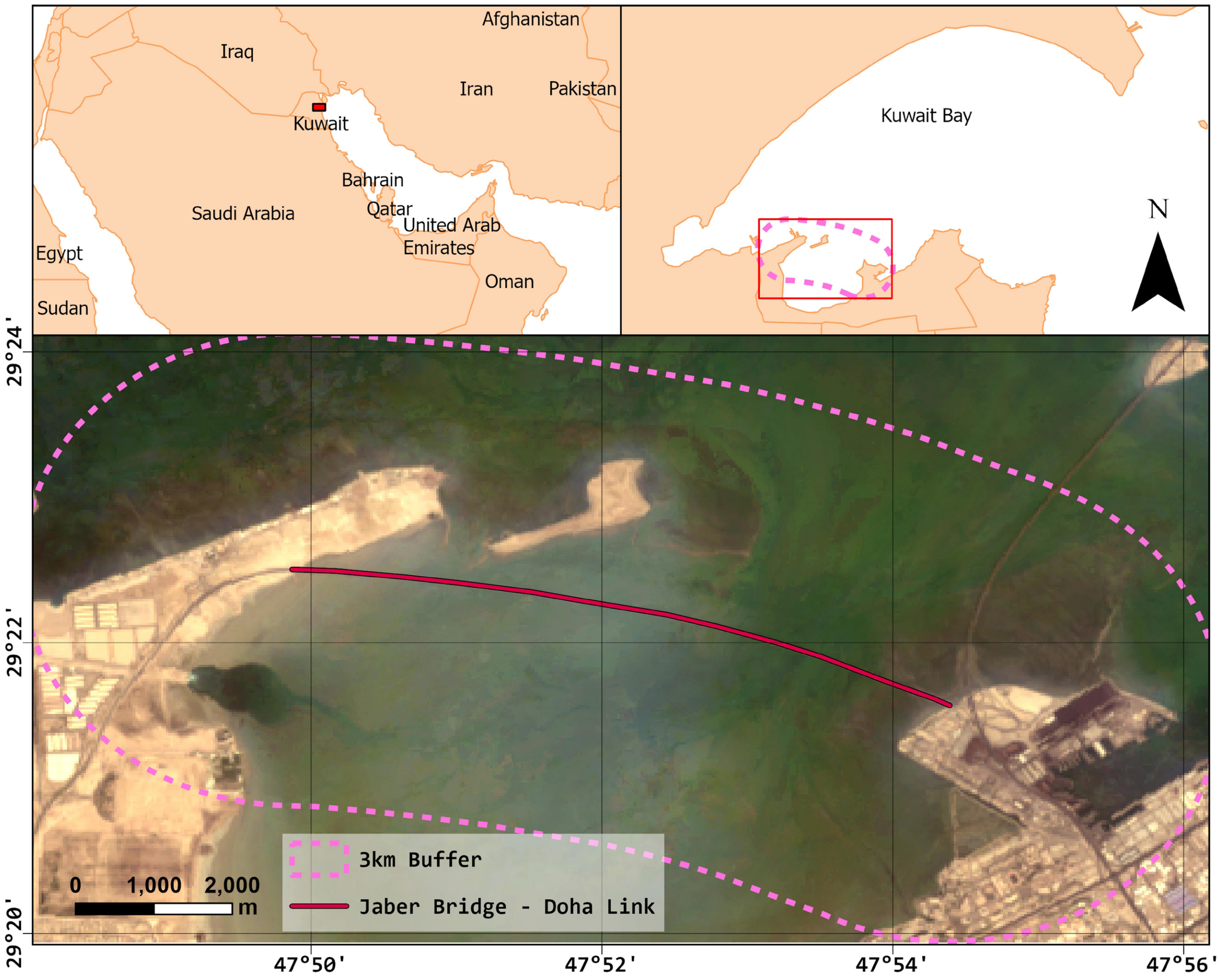

Figure 4. The Doha link section of the Sheikh Jaber Al-Ahmad Al-Sabah causeway and the defined study area boundaries.

4. Methodology

Figure 5 shows the work performance achieved during the study.

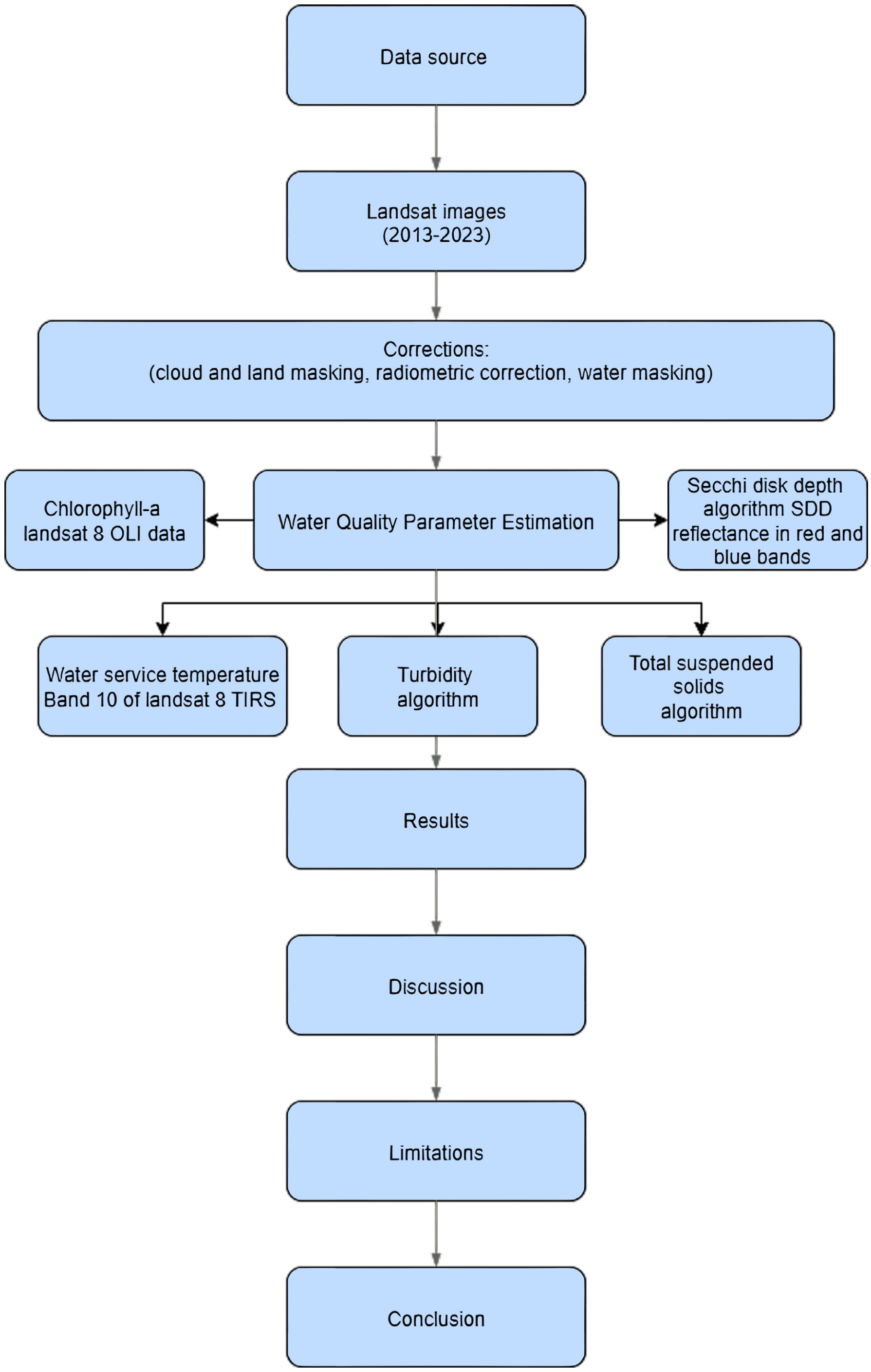

Figure 5. A flow chart showing the work performance implemented during the study.

4.1. Defined Study Periods

The study examines the effects of the Doha Link construction on water quality in Kuwait Bay. It focuses on three temporal phases:

1) The first phase is before construction. This includes data from July 2013. It shows baseline conditions before construction started.

2) The second phase is during construction. It encompasses the period from July

2014 to July 2018. It monitors any changes in water quality during construction.

3) The third phase is after construction. It encompasses the period from July 2019 to July 2023 and aims to evaluate recovery or persistent effects following construction.

July is selected annually to reflect seasonal variations. July has stable weather and little freshwater input from rain. This reduces outside effects on water quality [23]. The month of July was specifically selected because of the weather conditions. For example, in Kuwait's climatic history, July is known for extremely hot weather, so this weather affects the outcomes of the study. Therefore, future studies should consider more seasons and months, such as winter and spring seasons. This will help to enhance results.

4.2. Satellite Data Acquisition

4.2.1. Data Sources

This study used satellite images from Landsat 8. It included data from the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Landsat 8 provides multispectral images with a 30-meter resolution. This applies to visible, near-infrared (NIR), and shortwave infrared bands (SWIR). The thermal infrared (TIR) bands have a 100-meter resolution, resampled to 30 meters [24]. The satellite revisits every 16 days. This makes it useful for tracking environmental changes over time.

Due to time and cost constraints, in-situ water quality sampling was not conducted. While this limits direct validation of remote sensing results, the study compensates through the use of well-established algorithms and literature-based coefficients. Future work should integrate field measurements for greater calibration and validation accuracy.

4.2.2. Selection of Imagery

Images were selected annually for July from 2013 to 2023. This includes the preconstruction, construction, and post-construction phases of the Doha Link. July signifies summer in Kuwait. It experiences minimal precipitation and consistent weather patterns [25]. This reduces the impact of seasonal variations on water quality.

The images met specific criteria. Cloud cover was below 20 percent to reduce the effects of clouds. Therefore, this has a direct impact. For example, clouds can block visibility, which acts as a barrier. Only Level-1 Precision and Terrain-corrected images were utilized for geometric accuracy. The images were collected around mid-July annually to ensure consistency. Eleven images, one for each year, were chosen for analysis.

4.3. Preprocessing Steps

4.3.1. Cloud and Land Masking

Cloud shadows can reduce the accuracy of water quality estimates from satellite images [26].

The Quality Assessment (QA) band from Landsat 8 Level-2 products was used to remove these effects. Bitmask flags for cloud and cloud shadow were used to identify and exclude affected pixels [27].

Land areas were removed using the Normalized Difference Water Index (NDWI). This index is calculated using the green and near-infrared bands [28].

$$\frac{(\text{Green} - \text{NIR})}{(\text{Green} + \text{NIR})}$$

Pixels with NDWI values greater than zero were identified as water. Other pixels were excluded to focus on water areas [29].

4.3.2. Radiometric Corrections

Radiometric corrections were used to convert digital numbers to top-of-atmosphere (TOA) reflectance. These were subsequently converted to surface reflectance using scaling factors from the metadata files [30]. Surface reflectance products account for atmospheric effects, improving water quality measurements more accurately [31].

The reflectance values were adjusted using this equation (source: [30] [31]):

$$\begin{aligned}&\text{Surface Reflectance}\\&= \text{Reflectance Multiplier} \times \text{DN} + \text{Reflectance Additive}\end{aligned}$$

Where DN represents the digital number values of the pixels.

4.3.3. Water Masking

The NDWI thresholding method was used to separate water bodies from land and non-water features. This ensures that the analysis focuses only on aquatic environments in the study area [32].

4.3.4. Potential Biases and Corrections in Remote Sensing Data

Remote sensing datasets, such as those obtained from Landsat 8 satellites, may inherently contain biases caused by atmospheric disturbances (e.g., aerosol interference, water vapor, and cloud coverage) and sensor inaccuracies (e.g., calibration issues, sensor drift, and spatial resolution limitations). Such biases can influence the accuracy of the retrieved water quality parameters.

To mitigate atmospheric biases, this study used Landsat 8 Level-2 surface reflectance products processed using standard atmospheric correction methods (Landsat Surface Reflectance Code-LaSRC). LaSRC effectively corrects for aerosol scattering and absorption, significantly minimizing atmospheric interference (Vermote *et al.*, 2016).

Additionally, cloud and cloud-shadow pixels, which could affect data accuracy, were systematically identified and excluded using the Quality Assessment (QA) bands provided with Landsat 8 imagery (Zhu *et al.*, 2015).

Regarding sensor inaccuracies, Landsat sensors undergo routine calibration and validation, which helps maintain their accuracy and reliability (Chander *et al.*, 2009). However, limitations remain due to the sensor's spatial resolution (30 m).

Such a resolution could lead to mixed pixels, especially near coastal zones or areas with complex surface features, causing minor inaccuracies in water quality estimation.

Although significant steps were taken to reduce these biases, minor residual uncertainties may persist and should be considered when interpreting the results presented in this study.

4.4. Water Quality Parameters Estimation

4.4.1. Remote Sensing Reflectance (RSR) Calculations

Remote Sensing Reflectance (RSR) is an important parameter in ocean color remote sensing. It shows the ratio of water-leaving radiance to downwelling irradiance above the water surface [33]. RSR is used to calculate water quality parameters using bio-optical algorithms. RSR was calculated for the required spectral bands using surface reflectance values. The formula is (source: [34]):

$$\text{RSR} = \text{Surface Reflectance}/\pi$$

This conversion adjusts for bidirectional reflectance distribution function (BRDF) effects and standardizes the reflectance for analysis [34].

4.4.2. Chlorophyll a Estimation

Chlorophyll a concentration was calculated using the three-band ocean color algorithm (OC3) modified for Landsat 8 [15]. The algorithm uses the ratio of reflectance in the blue and green bands.

The formula is (source: [15]):

$$\text{Chlorophylla} = 10^{(a0+a1R+a2R2+a3R3+a4R4)}$$

where:

$$\log_{10}\frac{(\text{Rrs}(\text{Blue}))}{(\text{Rrs}(\text{Green}))}$$

The coefficients a0, a1, a2, a3, and a4 were taken from [35] to adapt the algorithm for Landsat 8 OLI data.

4.4.3. Total Suspended Solids (TSS) Estimation

TSS was calculated using the [36] algorithm.

The formula is (source: [36]):

$$\frac{A \times \text{Rrs}(\text{Red})}{1-(C \times \text{Rrs}(\text{Red}))}$$

The coefficients A and C were set based on values recommended for turbid waters. These were adjusted for the optical properties of Kuwait Bay [36].

4.4.4. Turbidity Estimation

Turbidity was derived using the algorithm by [37], which is suitable for a wide range of turbidity values (source: [37]):

$$\frac{a \times Rrs(Red)}{1-\left(\frac{Rrs(Red)}{b}\right)}$$

where a and b are empirical coefficients, whose values were selected based on calibration with in-situ data from similar environments [37].

4.4.5. Secchi Disk Depth (SDD) Estimation

SDD was calculated using the algorithm developed by [38], which correlates SDD with the reflectance ratio in the red and blue bands (source: [39]):

$$\left(\frac{Rrs(Red)}{Rrs(Blue)}\right)^{b}$$

Coefficients a and b were modified according to regional optical characteristics and existing literature [39].

4.4.6. Water Surface Temperature (WST) Estimation

WST was calculated using the thermal infrared band 10 of Landsat 8 TIRS [40]:

The formula is (source: [41]):

$$K_2 \div \ln\left(\frac{K_1}{L_\lambda}+1\right)-273.15$$

Here, K1 and K2 are calibration constants from the metadata, and L is the spectral radiance. The result is in degrees Celsius. In [41], preprocessing steps were performed (emissivity adjustments and atmospheric correction) before applying this method.

4.5. Data Analysis

Google Earth Engine (GEE) [42] and ArcGIS Pro are cloud-based platforms that handle large-scale geospatial analysis [16]. Statistics for water quality parameters, including mean, median, and standard deviation, were calculated using Microsoft Excel and Python. ArcGIS Pro was also used to create spatial maps for these parameters. In addition, [42] and its code editor were used for data processing, parameter estimation, and exporting the results.

5. Results

5.1. Colored Dissolved Organic Matter (CDOM)

CDOM levels changed noticeably during the study periods. The mean CDOM concentrations increased overall from the pre-construction to the post-construction period, with some yearly variations. In terms of Colored Dissolved Organic Matter (CDOM), the following data are relevant. Before construction in 2013, the mean CDOM concentration was 0.85 μg/L. On the other hand, CDOM levels changed in the construction period (2014 to 2018). Also, CDOM levels increased to more than 1.2 μg/L after the construction period. The highest mean was in 2020 at 1.27 μg/L

(Figure 6 and Figure 7). Construction may indirectly change CDOM by altering water movement and the transport of organic matter [43].

Without the on-site data on organic matter, it is hard to check if the construction caused the changes that occurred in the study area.

5.2. Chlorophyll a

Chlorophyll a levels changed significantly during the study period. These changes indicate variations in phytoplankton biomass. For example, before construction in 2013, the mean concentration was 2.53 µg/L. During construction, there was a drop in 2015 to 0.76 µg/L and in 2018 to 0.82 µg/L. After the construction period, many peaks in chlorophyll a concentration were observed compared with the previous period. The maximum peak was measured in 2020 with a concentration of 35.01 µg/L, which may be an indication of an algal bloom. This high concentration could have occurred due to changes in the environment after construction (Figure 8 and Figure 9).

5.3. Total Suspended Solids (TSS)

The mean value of TSS concentration was 23.48 µg/L before construction in 2013. During construction, a peak was noticed in 2015 with 35.84 µg/L, which may have happened due to sediment disturbance from the construction processes. In the post-construction period, the level of TSS changed dramatically because of sediment resuspension from dredging and pile driving (Figure 10 and Figure 11).

5.4. Turbidity

Turbidity levels measured vary among the periods of the study. Before construction, the mean turbidity value was 8.76 NTU and increased to 35.8 NTU in 2015 during the construction, which is considered a sign of the presence of particles in the water. After construction, the rate of change in turbidity level was similar to the rate during construction (Figure 12 and Figure 13).

5.5. Water Surface Temperature (WST)

After observing WST levels, a clear increase was noticed during and after construction periods compared to the year 2013. WST before construction was 32.46˚C and increased to 35.16˚C and 36.00˚C in 2017 and 2023, respectively (Figure 14 and Figure 15).

5.6. Secchi Disk Depth (SDD)

There was a significant change in SSD values after the analysis. Before the construction in 2013, the mean SDD value was 1.3 meters. On the other hand, the value decreased to 1.25 meters during the construction in 2016. Moreover, the drop in value continued after the construction period and reached 0.97 meters in 2020. The results of SDD confirm the results of turbidity and TSS levels (Figure 16 and Figure 17).

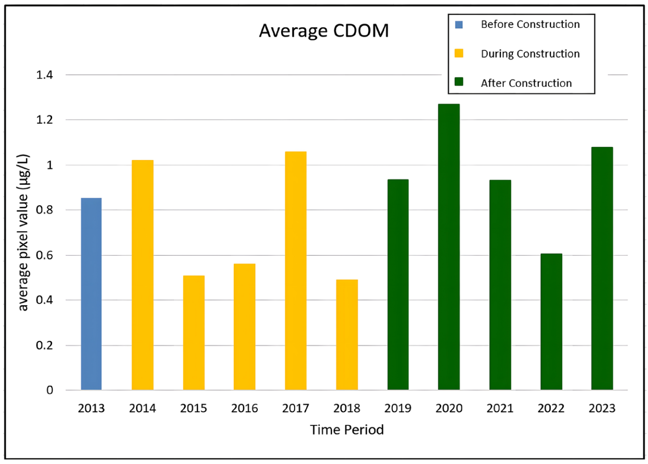

Figure 6. Temporal activity for CDOM.

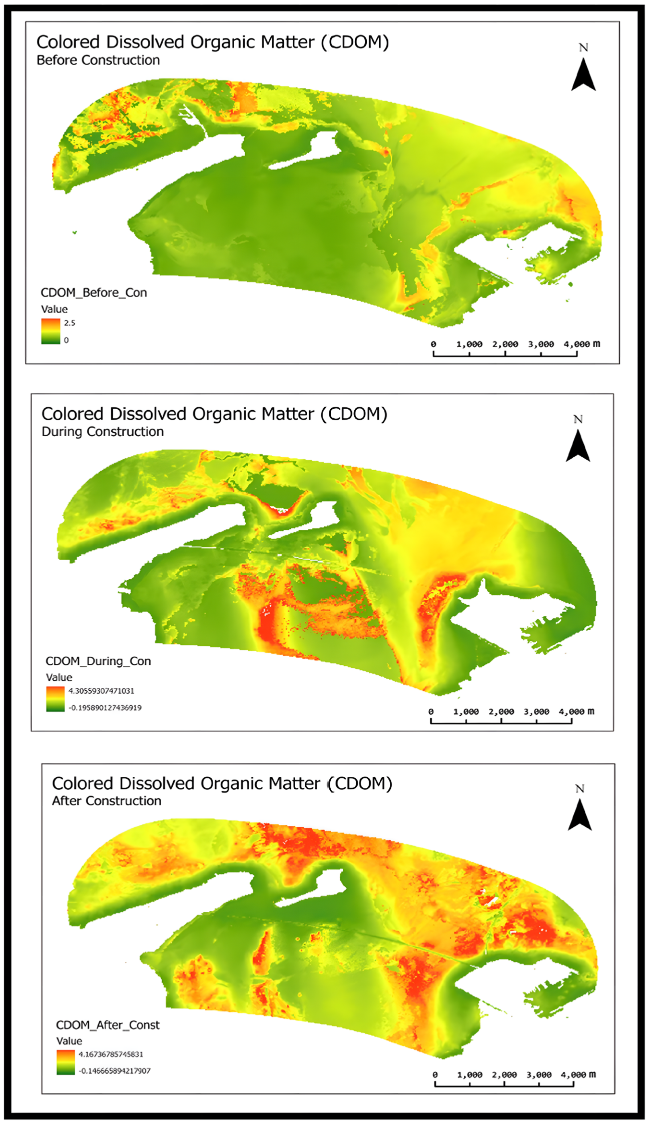

Figure 7. Colored dissolved organic matter concentration before, during, and after.

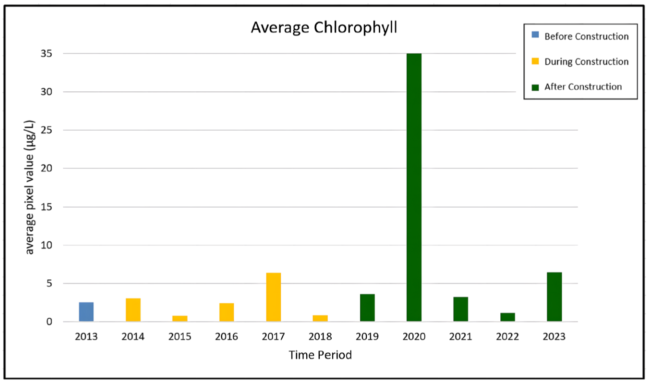

Figure 8. Temporal activity of chlorophyll.

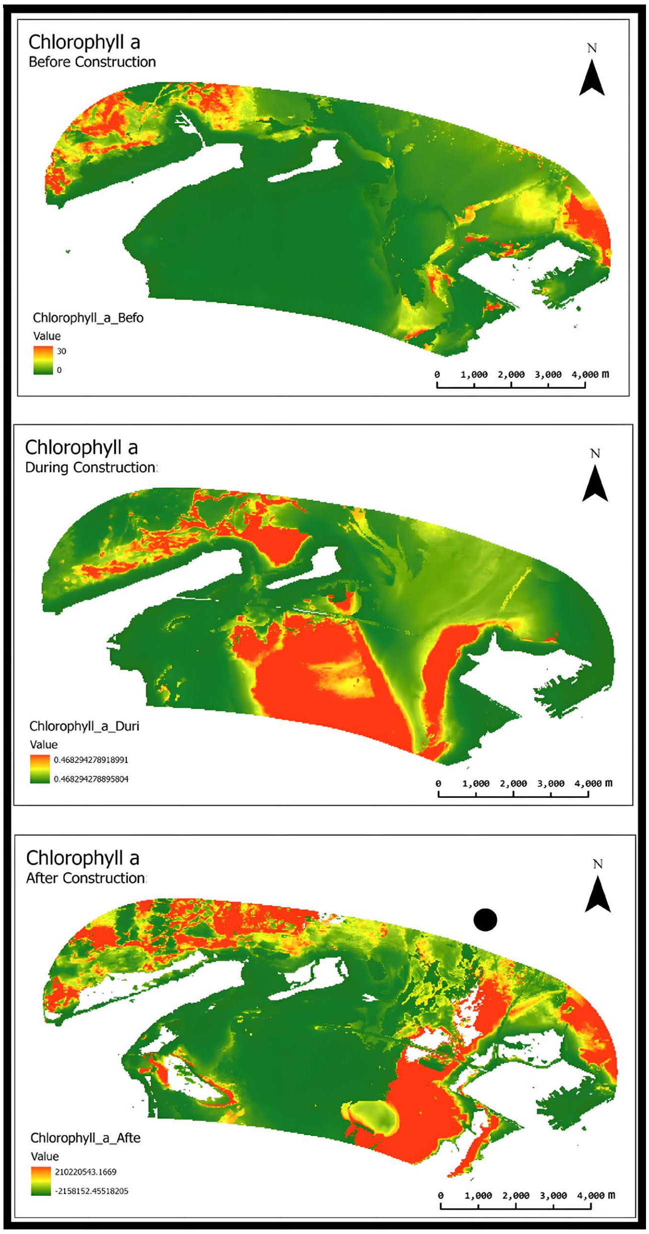

Figure 9. Chlorophyll a concentration before, during, and after.

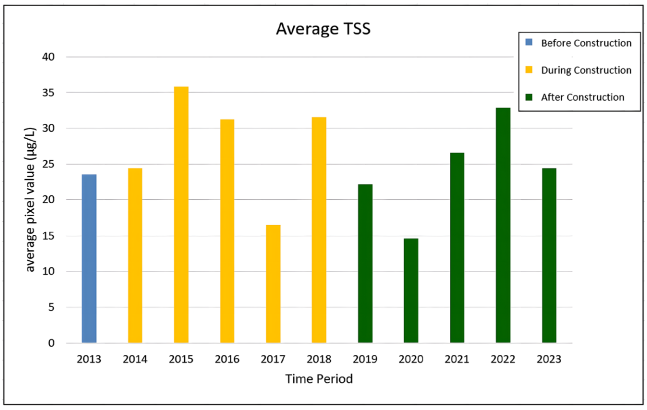

Figure 10. Temporal activity of TSS.

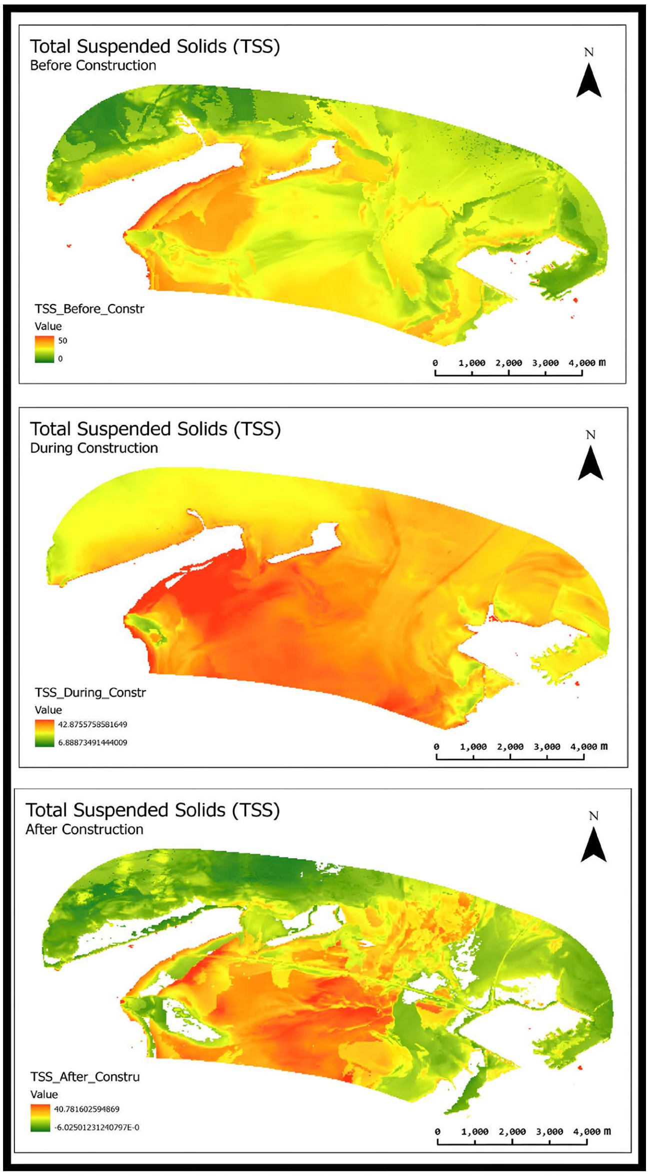

Figure 11. Total suspended solids concentration before, during, and after.

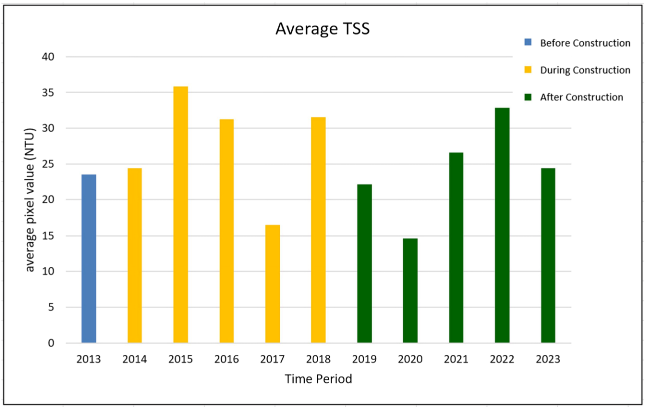

Figure 12. Temporal activity of turbidity.

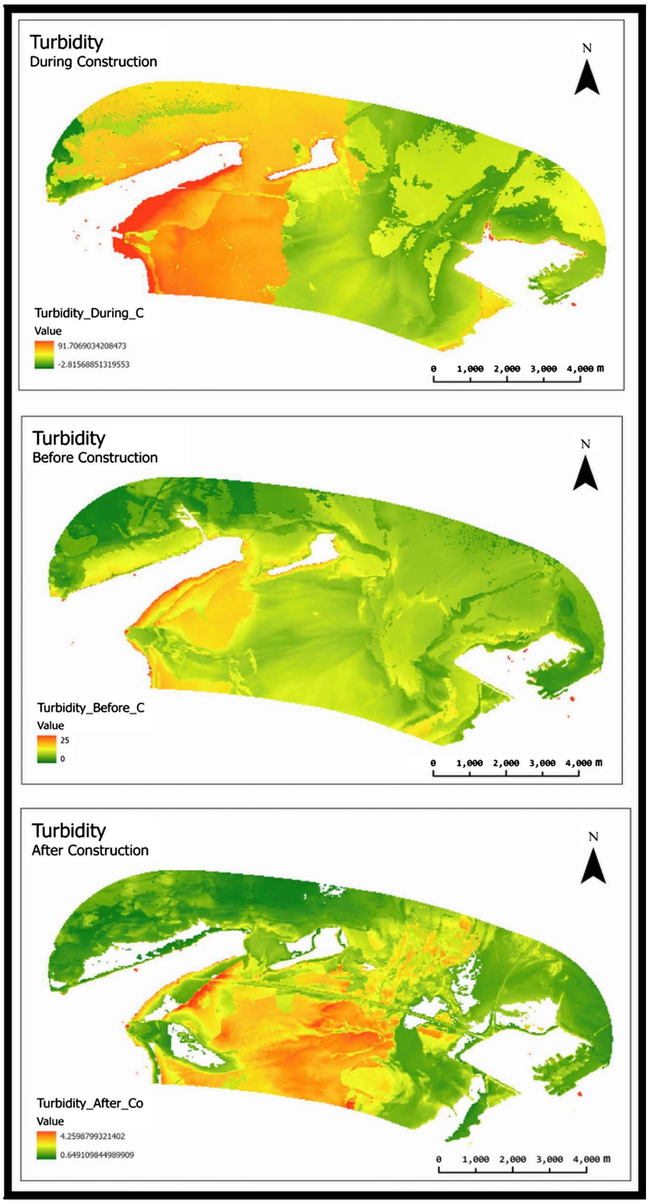

Figure 13. Turbidity concentration before, during, and after.

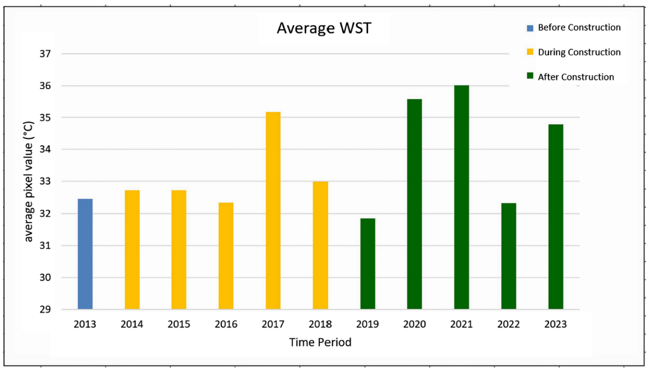

Figure 14. Temporal activity of water surface temperature.

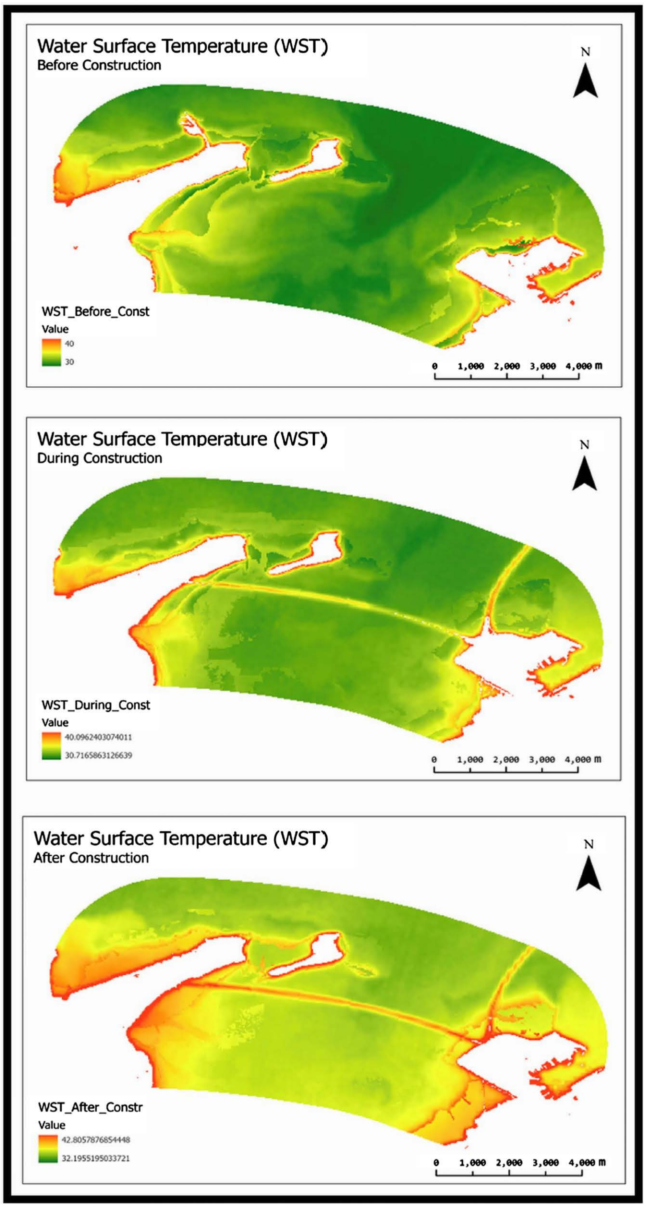

Figure 15. Water surface temperature concentration before, during, and after.

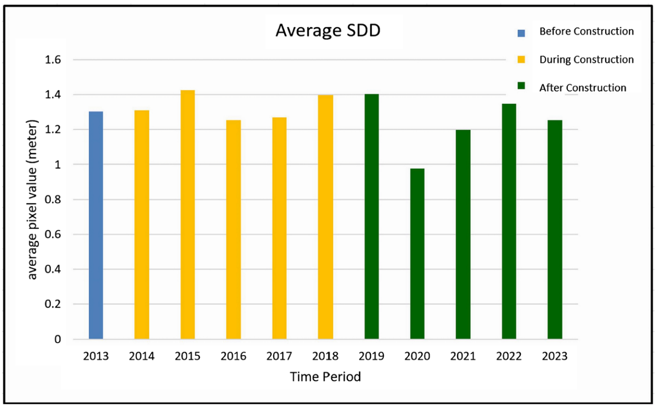

Figure 16. Temporal activity for Secchi disk depth.

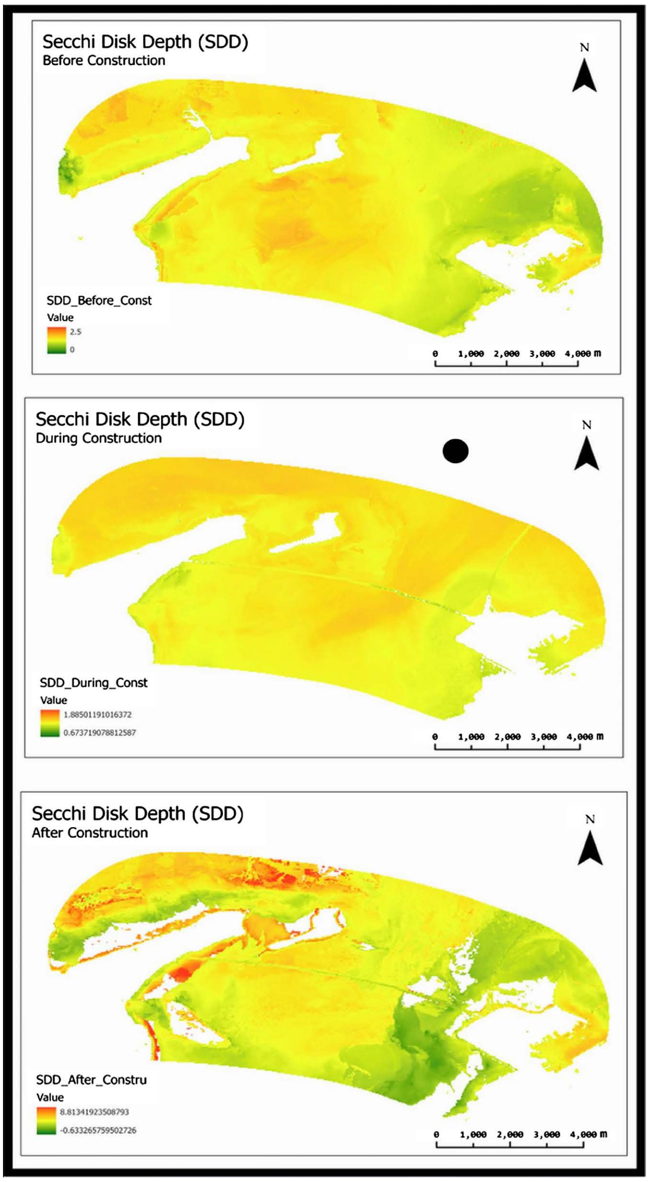

Figure 17. Secchi disk depth concentration before, during, and after.

6. Discussion

This section discusses the findings derived from the study; it represents an interpretation of the findings within the context of the relevant literature examined in this study. The results of the study found that throughout the construction process, many changes were identified in all of the variables. The study also confirmed that, in the case of large-scale coastal construction projects, there is a direct implication on the local marine environments, and these were clearly identified in the coastal Al-Doha Kuwait Bay ecosystems. Significant changes were identified in variables like CDOM, Chlorophyll a, TSS, SDD, Turbidity, and WST. Similarly, after the construction, Colored Dissolved Organic Matter (CDOM) was identified to be higher. This increase occurred because of the altered water movement due to the construction activities; likewise, fluctuation levels were identified in the case of Chlorophyll a. For example, it was sometimes high, then less, and this change again is most probably because of the changes occurring, both within the context of natural and man-made influences.

Based on the findings, it would also be reasonable to stress that diverse man-made activities that have a direct impact on water quality should be controlled, particularly those that impact the marine environment in Kuwait. For example, since the Al-Doha causeway was constructed, it has been passing through sensitive marine habitats and therefore has been constantly influenced by activities like dredging, land reclamation, and pile driving, all of which undoubtedly continue to have an impact on enhancing turbidity, sedimentation, and the constant disruption of benthic habitats. The findings from the investigation clearly confirm the direct need for conservation efforts and measures to be undertaken in order to prevent damage to the marine ecosystem and the marine environment as a whole.

While significant changes were identified in water quality parameters such as CDOM, Chlorophyll a, TSS, SDD, Turbidity, and WST, the interpretation of these results must acknowledge the potential minor residual biases inherent in remote sensing approaches. Such biases include possible atmospheric interference and spatial resolution limitations of the Landsat 8 imagery. Future studies could benefit from complementary *in situ* measurements or higher-resolution sensors to further validate and refine these observations.

7. Conclusions and Recommendations

The infrastructure construction project, such as the Jaber Al-Ahmad Causeway, can impact the marine environment from activities like dredging and land reclamation that will surely increase turbidity and other factors. Modern satellite approaches offer wide and frequent data coverage at a lower cost. Landsat 8, for example, can be used to track important indicators such as chlorophyll a, turbidity, suspended particulate matter, and sea surface temperature. Indices such as "Total Suspended Solids (TSS), Turbidity, Secchi Disk Depth (SDD), Water Surface Temperature (WST), Suspended Particulate Matter (SPM), and Normalized Difference Water Index (NDWI)" are used to compare the changes in water quality in this area before, during, and after the construction of Jaber Al-Ahmad Causeway. Although Landsat 8 provided reliable and valuable insights into environmental changes, further validation using field measurements and higher-resolution satellite data is recommended to confirm and enhance these remote sensing results.

Limitation Regarding Environmental Parameters

While this study focused primarily on parameters detectable through Landsat 8 imagery—such as Chlorophyll-a, Total Suspended Solids (TSS), Turbidity, Secchi Disk Depth (SDD), Water Surface Temperature (WST), and Colored Dissolved Organic Matter (CDOM)—it did not explicitly address other critical environmental factors such as dissolved oxygen (DO) and salinity. Both DO and salinity play significant roles in determining the overall ecological health and stability of marine ecosystems. The omission of these parameters may limit the comprehensive understanding of ecosystem dynamics, especially since construction activities (like dredging and land reclamation) can directly influence oxygenation and salinity gradients within coastal waters.

The results showed the impact of the bridge on the water environment in the bay, especially during the construction period. Water surface temperature is the factor affected. Field data on water quality, nutrients, and biological indicators should be collected. This can validate remote sensing and provide more detailed insights. Images from more months or sensors with higher frequency should be analyzed. This can capture short-term events and seasonal changes. Models should be used to simulate how construction changes water circulation. These can show how sediments and nutrients are affected. More environmental factors, like dissolved oxygen and salinity, should be included. This will help to assess ecosystem health more adequately.

Future research should prioritize integrating additional essential water-quality parameters, particularly dissolved oxygen and salinity. Complementary *in situ* measurements or advanced remote-sensing methods (e.g., hyperspectral imagery or integrated sensors on drones or autonomous monitoring buoys) can provide a more robust understanding of ecosystem health. Combining these datasets would enable researchers and policymakers to formulate more comprehensive and informed environmental management strategies.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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