Seasonal Water Quality Assessment Using Remote Sensing in Al Rafisah Dam, United Arab Emirates

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Keywords: Remote Sensing, Water Quality, Turbidity, Chlorophyll-a, Total Suspended Matter, Colour Dissolved Organic Matter, Sentinel-2.

Water bodies differ in their chemical, biological and physical properties. These properties determine their Abstract: quality, and sequentially, their applications. Conventional surface water quality analysis involves timely, costly, and intensive field and laboratory work. Remote sensing coupled with a geographic information management system (GIS) can offer an alternative to estimating water quality in remote or inaccessible locations. The main objectives of this study are to estimate chlorophyll-a, colour dissolved organic matter (CDOM), total suspended matter (TSM) and turbidity using remote sensing methods and to display them in temporal distribution maps. In this research, quantitative methodology was used to calculate the four water quality parameters using Sentinel-2 images of the Al Rafisah Dam in Sharjah, United Arab Emirates during the months of February, April, August and December of 2021. The Case 2 Regional Coast Colour (C2RCC) processor in the Sentinel Application Platform (SNAP) developed the equations and performed the calculations for chl-a, CDOM and TSM. ArcGIS Pro software was used for estimating turbidity with the normalized difference turbidity index (NDTI), as well as creating the spatio-temporal distribution maps. Overall comparative evaluation of the concentration patterns showed that the parameters selected for the study are interrelated, yet may vary depending on seasonal variations and human activities. Water quality research using remote sensing and GIS plays an important role in encouraging researchers to conduct more studies in unattainable sites or understudied areas such as the Al Rafisah Dam.

1 INTRODUCTION

Water bodies differ in their chemical, biological and physical properties. These properties determine their quality and their applications. Optical parameters of water quality include chlorophyl-a, colour dissolved organic matter, total suspended matter, and turbidity, which can affect water clarity, colour or algal content. Salinity, dissolved oxygen (DO), temperature, etc., on the other hand are non-optical parameters that do not necessarily affect the appearance (KC et al., 2019).

The main targets of this research are to (1) use appropriate satellite data to monitor water quality parameters of the study area, (2) to identify water quality parameters to be studied as per the study site and available data, and (3) to evaluate the results of the parameters based on the seasonal variations.

Contamination of water bodies is rampant due to a combination of natural and human-induced factors.

Monitoring water quality is critical to the continual existence of flourishing life and healthy environments, especially because water is largely utilised for drinking, recreation and agriculture (Khan et al., 2021).

Since the emergence of remote sensing, there have been various applications and usages of satelliteretrieved images. A topic that is being increasingly researched nowadays is the use of remote sensing in assessing the quality of water. Satellite earth observation data may be utilised to overcome the constraints of traditional water quality methodologies. Conventional surface water quality analysis involves timely, costly, and intensive field and laboratory work. Remote sensing coupled with GIS offers an alternative method to the estimation of water quality parameters in remote locations or where field samples have not been gathered.

Remote sensing is beneficial for long term investigations. Several studies have found that charting and observing water quality can help

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Alserkal, A., Alblooshi, A. and Al-Ruzouq, R. Seasonal Water Quality Assessment Using Remote Sensing in Al Rafisah Dam, United Arab Emirates. DOI: 10.5220/0012563900003696 Paper published under CC license (CC BY-NC-ND 4.0) In Proceedings of the 10th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2024), pages 112-119 ISBN: 978-989-758-694-1; ISSN: 2184-500X Proceedings Copyright © 2024 by SCITEPRESS – Science and Technology Publications, Lda. improve regional and largescale assessments (Abdullah et al., 2017; Acharya et al., 2019, Mucheye et al., 2022; Suet al., 2008).

Seleem et al. (2022) adopted the Case 2 Regional Coast Colour (C2CRR) atmospheric correction method to monitor the physical features of various water parameters such as chl-a, TSM and aquatic reflectance. Satellite data was used to investigate seasonal variance by comparing water quality over the dry and wet seasons.

Furthermore, a new era of spaceborne hyperspectral imaging has just begun with the recent availability of data from PRISMA launched by ASI. Niroumand-Jadidi et al. (2020) makes use of PRISMA level 2D imagery that were tested for their ability to retrieve typical water quality measures such as TSM, chl-a and CDOM. In their findings, they show that PRISMA level 2D imagery has a strong potential for mapping water quality indicators.

Another study made use of Sentinel-3/2 and Landsat-8 to retrieve chl-a, TSM, CDOM in various water types in Egypt. The study validated the usefulness of the visible and near-infrared (NIR) bands in predicting chlorophyll-a in waters. Using the C2RCC, the concentration of chl-a in the visible and NIR wavelengths revealed the amount of algae in the region (Masoud, 2022).

A paper by Ouma et al. (2020) also used Sentinel-2 to determine the same water quality parameters for the Chebara Dam in Kenya. They concluded that the satellite is capable of monitoring inland waterways and reservoirs for water quality.

Many studies have shown that the remote sensing approach can be used to estimate and predict the levels of turbidity, DO, chl-a, and heavy metals in water using Machine Learning (ML) Algorithms. These include the supervised processes; support vector machine and artificial neural networks, and unsupervised processes; principal component analysis. Ma et al. (2021) investigated turbidity of lakes by using Sentinel-2 satellite images with ML.

Water quality mapping utilising GIS and remote sensing is critical in today's environment. It is an effective instrument for environmental monitoring, resource management, public health, and scientific study. These technologies help to make educated decisions, conserve ecosystems, provide clean drinking water, respond to emergencies, and build successful policies by delivering reliable, real-time data on water quality. In an era when water resources are being threatened by pollution, climate change, and rising demands due to growing populations, the capacity to map and analyse water quality geographically and temporally is critical for the long-term management and protection of this crucial resource.



Figure 1: Study Area

The main objectives of this study are (1) to estimate chlorophyll-a, colour dissolved organic matter (CDOM), total suspended matter (TSM) and turbidity from Sentinel-2 images of Al-Rafisah Dam using ArcGIS Pro and Sentinel Application Platform and (2) to display them in spatio-temporal distribution maps for evaluation and comparison.

Water quality distribution maps will show the spatial distribution and temporal results of chl-a, CDOM, TSM and turbidity values in different months of 2021. These parameters were chosen due to their applicability and extensive use in remote sensing applications (Bangira et al., 2024; Virdis et al., 2022).

2 STUDY AREA

The study area selected for the project is the Al Rafisah Dam in Sharjah, United Arab Emirates, shown in Figure 1. It is located along Sharjah-Khor Fakkan highway between Al-Hajar Mountains that runs down to the city of Khor Fakkan on the east coast of Sharjah with coordinates 25° 21′ 0″ N, 56° 18′ 0″ E. It has an area of 10684 m2. Its elevation is roughly at around 197 meter or 649 feet.

Al Rafisah Dam is an area rich in local flora and fauna, and attracts many visitors during trips within the country. Visitors of the dam can take part in a number of touristic activities. Surrounding the site are several eateries, archaeological spots, and a hiking trail. Aside from offering spectacular views, the waterbody is used for boating activities and kayaking.

This paper focuses on assessing water quality in Al Rafisah Dam because it is an unprecedented subject matter that has not yet been investigated.

3 DATA USED

Given that several previous studies relied on Sentinel-2 satellite imagery to monitor and estimate water quality parameters, it was chosen as the primary data source for this research. Copernicus Open Access Hub was used to download Sentinel-2 Level 1C imagery containing the Al Rafisah Dam (Table 1). The criteria used to locate images of the dam included S2MSI1LC as product type and 5% of cloud coverage within the year 2021. Four dates were used to compare the results between the months of February, April, August and December.

4 METHODOLOGY

In this research, quantitative methodology involving deep learning equations and numerical indices were used to evaluate the chlorophly-a, CDOM, TSM and turbidity of Sentinel-2 images in Al Rafisah Dam. The programs utilized were ArcGIS pro version 3.1.0 and Sentinel Application Platform (SNAP). The Case 2 Regional Coast Colour (C2RCC) processor in the Sentinel Application Platform (SNAP) developed the equations and performed the calculations for chl-a, CDOM and TSM. ArcGIS Pro software was used for estimating turbidity with the normalized difference turbidity index (NDTI), as well as creating the spatiotemporal distribution maps.

SNAP was used for processing and estimating chl-a, CDOM, and TSM values. To start preprocessing of the images, the resample operator converted the spatial resolution of all satellite bands to a single pixel size (10m). The geometric subset operator was used to create a smaller image, and therefore require less computational resources for processing.

Next, atmospheric correction was applied; which is crucial in order to be able to separate different optically active constituents in water such as chlorophyll-a, TSM and CDOM. The retrieval of the optically active constituents is done in the form of C2RCC S2MSI processor, an algorithm based on a

Satellite and Sensor	Product Name	Product Level	Sensing Date
Sentinel 2 MSI	S2B_MSIL1C_20210217T064929_N0500_R020_T40R DP_20230603T172352.SAFE	Level 1C	February 17 2021
Sentinel 2 MSI	S2A_MSIL1C_20210423T064621_N0500_R020_T40R DP_20230602T234425.SAFE	Level 1C	April 23 2021
Sentinel 2 MSI	S2A_MSIL1C_20210821T064631_N0500_R020_T40R DP_20230216T134509.SAFE	Level 1C	Aug 21 2021
Sentinel 2 MSI	S2B_MSIL1C_20211224T065309_N0500_R020_T40R DP_20221226T173342.SAFE	Level 1C	December 24 2021

Table 1: Satellite and sensor data.

deep learning, neural networks approach. This processor required Sentinel-2 level 1C as source input.

With this, Sentinel-2 satellite imagery was downloaded and processed by geometric, radiometric and atmospheric correction within the aforementioned softwares. The complete methodology framework is illustrated in Figure 2.

4.1 Watershed

The pre-processing of the SRTM DEM (30m) from USGS was completed using the following ArcGIS Pro tools; fill, flow direction, flow accumulation, stream order, stream segmentation, catchment delineation, catchment polygon processing, snap pour point and slope. All of these processes were applied to the reconditioned DEM to increase the accuracy of Al Rafisah watershed delineation utilizing stream networks.

4.2 Water Quality

Sentinel 2 level 1C data was downloaded from European state agency website with 5% cloud coverage for four months in 2021; February, April, August and December and input to SNAP.

Processing parameters such as the salinity was set to 0.0001, since it is freshwater body, and the elevation was set to 197m as per the study area. Other parameters such as atmospheric ozone and air pressure at sea level will be set in our brush script specifically for each images as they changed in time. Finally, three-output data sets were selected; which are output normalized water leaving reflectance, output irradiance attenuation coefficients and output uncertainties. The following are the default equations within the C2RCC processor that computed chl-a and TSM (Doerffer, 2019):

Chl-a [mg m-3] =
$$21 \times a_{pig}(443)^{1.04}$$
 (1)

$$TSM = 1.7 \text{ x b}_{part}(443)$$
 (2)

The water leaving reflectance resulting from the C2RCC operator was also used to calculate chl-a indices with two empirical models; the band ratio of NIR over red and the maximum chlorophyll index (MCI), where the peak is at around NIR 705nm (Ansper & Alikas, 2019):

MCI = R705 - R665 - 0.53 * (R740 - R665)(3)

In-situ data was not collected and no existing field measurements were available for this study. Therefore, validating results and calibrating based on line regression for empirical models to extract the chlorophyll concentration could not be done.

The results were reprojected and exported as tiff format. Finally, these files were imported to ArcGIS Pro to create the final distribution map layouts for chla, CDOM and TSM.



Figure 2: Methodology framework.



Figure 3: Watersheds and drainage networks map.

In ArcGIS Pro, Sentinel-2 level 1C data was atmospherically corrected for the four months in 2021. Then, McFeeters (1996) normalized difference water (NDWI) index was calculated to detect the surface water bodies. Normalized difference turbidity index (NDTI) was used to estimate the turbidity in water bodies (Sankaran et al., 2023). The equation for each are as follows:

$$NDWI = (Green-NIR/Green+NIR)$$
 (4)

$$NDTI = (Red-Green/Green+Red)$$
 (5)

Next, binary raster classification was created for NDWI raster using the (greater_than) function to differentiate between water and non-water pixels. After that, a water body mask was created to extract the boundaries of the Al Rafisah waterbody. Finally, the NDTI raster was clipped with NDWI to extract the intersect part between both of them to have the turbidity product.

Final map layouts were produced to evaluate and compare the water quality results.

5 RESULTS AND DISCUSSION

Sentinel-2 MSI was suitable as the data source for this study considering its resolution and the area size of Al Rafisah Dam.

5.1 Watershed

The watersheds and drainage networks map is shown in Figure 3. The results of the watershed delineation show that the dam location is perfect because high and moderate streams end in the dam location, where the water can be collected.

5.2 Water Quality

Chl-a concentrations predicted from Sentinel 2 satellite images were done by two approaches. The first approach was from the C2RCC processing. Concentrations ranged from 0.0003 mg/m3 up to 29.5157 mg/m3. Figure 4 shows that February and December displayed higher maximum values, while minimum values for all months were between 0.0003

mg/m³ to 0.0007 mg/m³. In terms of the average concentrations, they were highest during the summer months of April and August. The lowest concentration was in February and the highest in April at 2.6936 mg/m³ and 11.8809 mg/m³, respectively. Maximum values can be seen towards the edges of the waterbody for all Chl-a distribution maps, as well as towards the dam in April. Higher temperatures during summer can create increased production and appearance of phytoplankton and Chl-a containing organisms.

The second approach used empirical models; first of which is the Band Ratios Model where Red Band 4 and NIR Band 5 are used (Figure 5). Mean values resulting from this method ranged from 0.8003 to 0.8202. MCI was the other empirical model and utilized Band 4 (Red), Band 5 (NIR) and Band 6 (NIR) (Figure 6). Mean values from MCI calculation ranged from 0.0033 to 0.0049. Average concentrations for these approaches followed similar trend with higher values in April and December and lower values in February and August. Like the C2RCC process, the highest average for both empirical models was found to be for the month of April.

The predicted concentrations of CDOM among all months ranged from 0.0001 m^{-1} to 0.763 m^{-1} (Figure 7). The concentration pattern corresponds to that of Chl-a. Higher average values were displayed for the summer months. Similarly, the winter months received the lowest values. The lowest mean concentration was in December and the highest mean in April at 0.1684 m⁻¹ and 0.5893 m⁻¹, respectively.

The concentrations for TSM retrieved from the satellite images ranged from 0.0101 g/m^3 to 37.6331 g/m^3 (Figure 8). February and December observed higher maximum values. The highest average concentrations were found in the cooler months of February, April, and December which were over 5 g/m³. The highest average concentration was once



Figure 4: Chl-a distribution maps using C2RCC for (A) February, (B) April, (C) August, and (D) December.



Figure 5: Chl-a distribution maps using band ratios for (A) February, (B) April, (C) August, and (D) December.



Figure 6: Chl-a distribution maps using MCI for (A) February, (B) April, (C) August, and (D) December.



Figure 7: CDOM distribution maps for (A) February, (B) April, (C) August, and (D) December.



Figure 8: TSM distribution maps for (A) February, (B) April, (C) August, and (D) December.

again in April at 5.7653 g/m³, whereas the drier, hotter month of August had the lowest average value at 3.9537 g/m^3 .

This trend could be a result of rainfall and tourist activity at the dam during these cooler months. The TSM maps display that maximum values are collected in the middle of the waterbody away from the edges.

The turbidity results shown in Figure 9 were obtained from NDTI calculations on ArcGIS Pro. Bands 3 (Green) and 4 (Red) from the satellite images were utilized. Higher NDTI values closer to 1 indicate turbid waters where reflectance is greater in the red band. Lower values nearer to -1 indicate clearer water. Turbidity values among all months ranged from -0.1151 to 0.0422. The lowest mean value was in February and the highest in August at -0.0848 and -0.0366 m⁻¹, respectively. The higher values were located in the southern part of the dam, as well as several spots towards the north, for all months. All mean NDTI values were just under 0.

According to Garg et al. (2017), values from around 0 to 0.2 are commonly categorized as moderate turbidity. Clear waters display values from 0 to -0.2, and highly turbid waters greater than 0.25.

Turbidity increases with existence of suspended and dissolved substances in fluids, thereby reducing the clarity. The amalgamation of chl-a, TSM and CDOM could be a cause for moderate turbidity in the dam.

In their study, Ouma, Noor and Herbert (2020) found that maps for chl-a concentrations and turbidity values in the Chebara Dam followed similar patterns. However, the concentrations for chl-a and TSM were higher than those found in the Al Rafisah Dam. Using Sentinel-2A and empirical models, concentrations for



Figure 9: Turbidity distribution maps for for (A) February, (B) April, (C) August, and (D) December.

chl-a ranged from 11 to 222 mg/m³, while TSM ranged from 35 to 574 g/m³.

A study on a Portuguese Estuary observed higher concentrations for the same four parameters during warmer months of 2020 compared to the winter months (Sent et al., 2021). These results were analogous to the average concentrations found at the dam.

6 CONCLUSION

The principal aim of this paper was to use appropriate remote sensing methods to monitor selected water quality parameters in the Al Rafisah Dam over several months in 2021. Specific targets were to identify which water quality parameters were to be studied. Additionally, to evaluate and compare the results based on the distribution maps that were created for each parameter and month. Sentinel-2 MSI was the chosen satellite and sensor due to its high spatial resolution and wide use in water quality monitoring. Chl-a, CDOM, TSM, and turbidity were also selected for the study due to their wide use in similar studies. The main objectives were achieved by estimating values and displaying distribution maps for the four water quality parameters.

Results showed that April had the highest average values for chl-a, CDOM, and TSM. August received the highest average for turbidity. Overall comparative evaluation of the concentration patterns showed that the parameters selected for the study are interrelated, yet may vary due to environmental and human influences.

This paper offered an unprecedented study on the water quality of the Al Rafisah Dam. Despite this, the

study observed some limitations that can be addressed in future works. It would be worthwhile to obtain ground truth from in-situ data for calibration and result validation. With these field measurements, models for estimating chl-a, CDOM, TSM, and turbidity can be tailored based on the requirements and objectives of the study. Additionally, future research could focus on a different selection of parameters or on comparing various satellite sensors as the data source. Water quality research using remote sensing and GIS plays an important role in encouraging researchers to conduct more studies in unexplored or unattainable locations.

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