Florida Transportation and Infrastructure

Monitoring Water Quality Along Southern Florida Seaports to Assess Impact on Coral Reef Tracts from Harbor Deepening Projects

 **Technical Report**

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# 1. Abstract

The U.S. Army Corps of Engineers (USACE) and National Oceanic and Atmospheric Administration (NOAA) National Marine Fisheries Service (NMFS) will be supervising a harbor deepening project in Port Everglades, Florida. The project raises concerns about potential impacts on the nearby Florida reef tract through increased turbidity and sediment from the dredging. To better understand these potential impacts, the NASA DEVELOP team created an interactive Google Earth Engine tool to help establish a historical baseline of water quality parameters and assist monitoring these parameters more frequently than traditional sampling. This Seaport & Harbor Area Resource Quality (SHARQ) tool incorporates remotely sensed data from Sentinel-2 Multispectral Instrument, Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper+, Landsat 8 Operational Land Imager, and Aqua Moderate Resolution Imaging Spectroradiometer. It allows users to view true color images and calculate water quality parameters, like turbidity and chlorophyll-a, for any given study area and time period from 1984 onward. The SHARQ tool also generate time series charts, allowing users to interpret changes in water quality over a given time range. The accuracy of the remotely sensed water quality parameter algorithms was determined using in situ data to calculate percent difference and root mean square error values (RMSE), which ranged from 0.32 to 0.58 error between sites. Using the SHARQ tool’s time series analysis feature, a baseline average turbidity metric of ~6.8 FNUs provides a historical baseline average for turbidity between September 2000 and 2020 and can assist in future decision-making for determining thresholds for turbidity.

**Key Terms**

Coral reef, turbidity, sediment, water quality, remote sensing, Landsat 8 OLI, Aqua MODIS, Sentinel-2, Florida

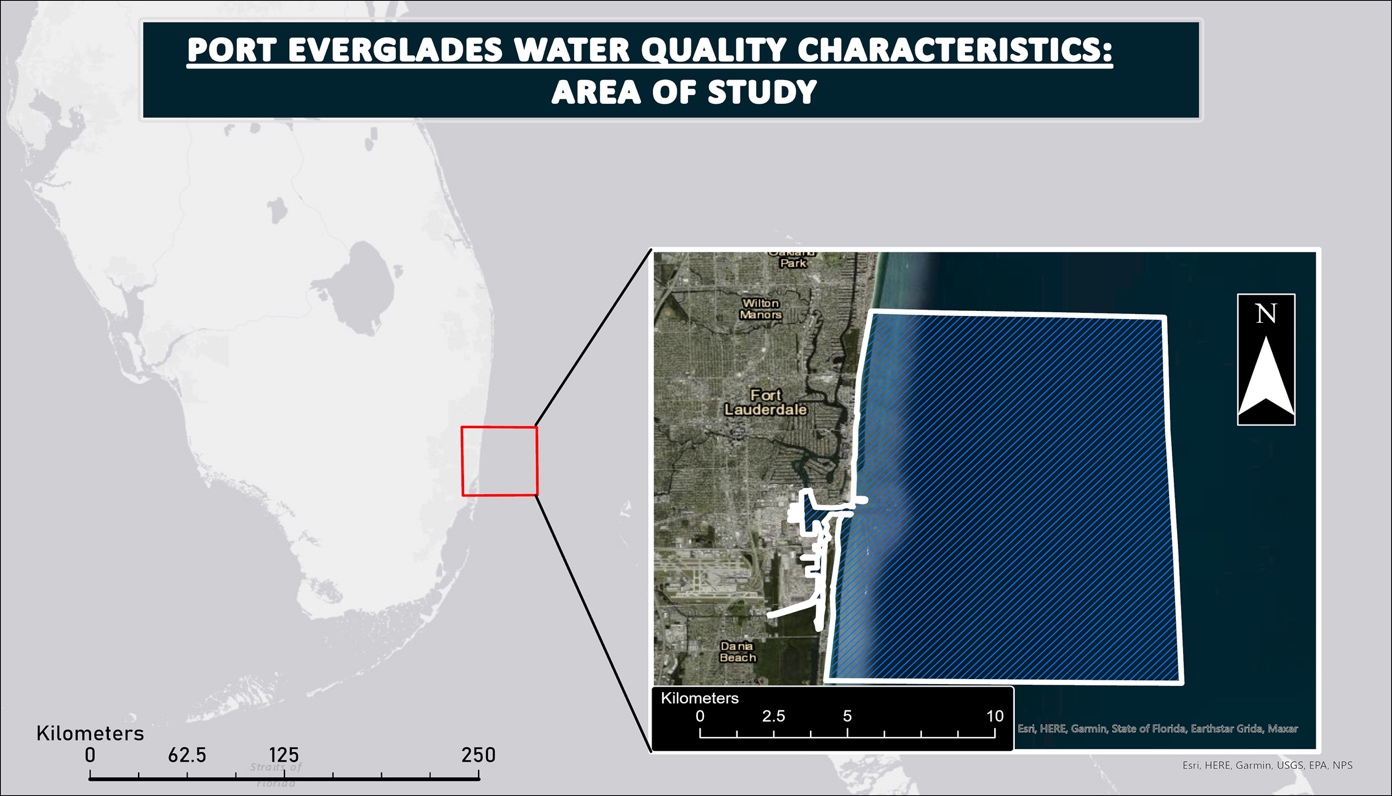
# 2. Introduction

***2.1 Background Information***

In early 2022, the U.S. Army Corps of Engineers (USACE) will begin a harbor deepening project in the Port Everglades seaport in southern Florida. The potential impact of this project on water quality, particularly turbidity, poses concern on the potential degradation of the surrounding coral reefs and reduction of ecosystem services the reefs provide. The DEVELOP Florida Transportation & Infrastructure team collaborated with the USACE, and the National Oceanic and Atmospheric Administration (NOAA) National Marine Fisheries Services (NMFS) to better understand the effects of this dredging project on coral reefs and water quality. Since reef recovery from mass mortality events is generally slow to non-occurrent at times, detection of long-term impacts on coral reefs is crucial to preventing major species loss (Erftemeijer et al. 2012). *In situ* monitoring of reef systems can be costly and time-consuming for studies with large temporal and spatial scopes. The limited availability of consistent and accurate *in* situ data calls for alternative research methods to be considered.

Alternatively, remote sensing allows researchers to assess water quality and reef health effectively, efficiently, and more frequently than with *in situ* monitoring alone. Relatively moderate-to-high-resolution satellite imagery such as those provided by the Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) programs can provide clear outlines of bright suspended sediments (Barnes et al., 2015) and can be used to assess dredging-induced turbidity (He, Hu, & Hu, 2014). However, there are limitations to using satellite imagery, such as the low repeat sampling frequency on Landsat instruments (16 days), resulting in large temporal gaps between measurements (Barnes et al., 2015). Such low repeat sampling frequency hinders turbidity event assessment, making it difficult to establish historical baseline conditions that can help distinguish between turbidity events and historically normal conditions (Barnes et al., 2015). Cross-validation between remotely sensed data and *in situ* data, along with correction for factors like atmospheric changes and attenuation are needed to enhance such remote sensing applications (Page, Kumar, & Mishra, 2018).

The team used Google Earth Engine (GEE), to create the Seaport & Harbor Area Resource Quality (SHARQ) interactive tool for evaluating water quality in the Port Everglades Seaport from 2000 to 2020. SHARQ allows for visualization of selected water quality parameters and the creation of time series charts that reflect how the parameters have changed over time. The tool utilized data from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI), Sentinel-2 Multispectral Instrument (MSI), Aqua MODIS, and Terra MODIS.



*Figure 1.* The study area focuses on the areas just off the Southern Florida ports of interest (Basemap: ESRI “Light Grey Canvas” & “Satellite Imagery” Layer Package, GARMIN, State of Florida, HERE, ArcGIS Pro).

***2.2 Project Partners & Objectives***

The United States Army Corps of Engineers (USACE) is an agency within the United States Army responsible for the engineering and construction of military and civil works projects across the nation. Primarily focused on infrastructure, USACE has provided communities with roads, dams, harbors, and power since 1802 (USACE, 2021). The National Oceanic and Atmospheric Administration (NOAA) Fisheries division is responsible for the monitoring, evaluating, and protecting of all marine life and habitat within the oceans of the United States. Both agencies are end-user partners that will use this project’s end products to monitor, track, and forecast the impacts of dredging on water quality variables, and the subsequent effects on coral reefs. The use of satellite imagery will allow the partners to detect water quality parameters over time and use such information to make more informed decisions to help mitigate harmful impacts on reefs from dredging.

# 3. Methodology

***3.1 Data Acquisition***

The methodology for this study is built upon techniques and practices executed by the Fall 2019 NASA DEVELOP Belize & Honduras Water Resources II team in their creation of the Optical Reef and Coastal Area Assessment (ORCAA) tool. The satellite imagery data used was acquired from the GEE data catalog. Specifically, the following data was used (Table 1): Landsat 5 TM Surface Reflectance Tier 1, Landsat 7 ETM Surface Reflectance Tier 1, Landsat 8 OLI Level 2 Surface Reflectance Tier 1, Sentinel-2 MSI Level 1C TOA Reflectance, and Aqua-Terra MODIS Level 3 Standard Mapped Images. Both Landsat and Sentinel data were used for true color images and to calculate turbidity, normalized difference turbidity index (NDTI), normalized difference vegetation index (NDVI), and colored dissolved organic matter (CDOM). Only Landsat data was used to calculate diffuse light attenuation (Kd(490)). In contrast, normalized difference chlorophyll-a index (NDCI) and in turn Chlorophyll-a (Chl-a) were calculated using Sentinel-2 imagery exclusively. The sea surface temperature band, available in Aqua and Terra MODIS, was used to determine sea surface temperature. In addition to these datasets, the team also used *in situ* measurements of turbidity and temperature sourced from the NOAA National Marine Fisheries Service, Habitat Conservation Division.

Table 1.

*Remote sensing data used in GEE.*

|  |  |  |  |
| --- | --- | --- | --- |
| **Sensor** | **Processing Level** | **Data Provider** | **GEE ImageCollection ID** |
| Landsat 5 TM | Surface Reflectance Tier 1 | United States Geological Survey (USGS) Earth Explorer | LANDSAT/LT05/C01/T1\_SR |
| Landsat 7 ETM+ | Surface Reflectance Tier 1 | United States Geological Survey (USGS) Earth Explorer | LANDSAT/LE07/C01/T1\_SR |
| Landsat 8 OLI | Level 2 Surface Reflectance Tier 1 | United States Geological Survey (USGS) Earth Explorer | LANDSAT/LC08/C01/T1\_SR |
| Sentinel-2 MSI | Level 1C TOA Reflectance | European Space Agency (ESA Open Access Hub) | COPERNICUS/S2 |
| Aqua MODIS | Level 3 Standard Mapped Image | NASA Ocean Biology Processing Group (OBPG) | NASA/OCEANDATA/MODIS-Aqua/L3SMI |

***3.2 Data Processing***

The outputs of this project were processed in Google Earth Engine. The water quality parameters calculated in this project included turbidity, NDTI, Chlorophyll-a, NDCI, NDVI, CDOM, and Kd(490). Apart from Sentinel-2 Level 1-C data, atmospheric correction was not conducted within GEE due to the availability of surface reflectance products in the GEE data library. Sentinel-2 Level 1-C data was atmospherically corrected using the MAIN algorithm developed by Page et. al (2019).

*3.2.1 Turbidity*

The turbidity function included in SHARQ is the same algorithm used by the Fall 2019 NASA DEVELOP Belize & Honduras Water Resources II team’s ORCAA tool. The function was developed during a previous effort by Sol Kim, Rafael Grillo Avila, and Xiaowei Wang at the University of California (UC), Berkeley under the guidance of Dr. Christine Lee. This team used the algorithm and associated coefficients described by Nechad, Ruddick, & Neukermans 2009 paper. The algorithm uses reflectance in the red and near-infrared range of the electromagnetic spectrum to estimate turbidity in Formazin Nephelometric Units (FNUs) (*Equation 1*).

(1)

In this function, AT and C are wavelength-dependent calibration coefficients and are the water leaving reflectance at a given wavelength. C is calibrated using standard Inherent Optical Property data, while nonlinear least-square regression analysis is used to find AT (Nechad et al., 2009). When comparing the outputs of their GEE algorithm to ACOLITE outputs for the same scene, Kim, Avila, and Wang achieved an R2 value of approximately 0.98, indicating a strong agreement between tools. This algorithm was applied to our Landsat image collection, comprised of data from Landsat 5, 7, and 8, with modified coefficient values to suit the sensor; as well as our Sentinel-2 image collection to provide turbidity data from 2000 – 2020.

*3.2.2 NDTI*

The Normalized Difference Turbidity Index (NDTI) (Lacaux et. al (2007), was used to identify areas of turbidity. Changes in the turbidity of the water affect spectral reflectance in the visible region greatly. The NDTI measures the ratio of reflectance in the green band to reflectance in the red band (Garg et. al, 2020). Clear water will have a much higher amount of reflectance in the green wavelengths than in the red wavelengths (Garg et. al, 2020). As turbidity increases, the amount of reflectance in the red band will increase and may even surpass the amount of reflectance in the green band. Negative values of NDTI represent clearer, less turbid water, while positive values represent more turbid water (Sekhon et. al, 2016). The following formula is used to calculate NDTI (*Equation 2*):

(2)

This algorithm was applied to both our Landsat image collection and the Sentinel-2 image collection to provide NDTI values from 2000 to 2020.

*3.2.3 NDCI & Chlorophyll-a*

The Chlorophyll-a function of our tool also shares the same function used for the ORCAA tool, derived from Mishra & Mishra (2012) (*Equation 3*). NDCI yields results with reflectance bounds of +1 and -1, allowing more isolated areas to be tested without the need for calibration of *in situ* data (Mishra et al., 2014).

(3)

From NDCI, the ORCAA tool derives chlorophyll-a concentration (*Equation 4*):

(4)

where a0, a1, and a2 are calibrated model coefficients (14.036, 86.115, and 194.325, respectively) derived from the non-linear fitting of observed chlorophyll-a data with NDCI values. Landsat satellites and their accompanying sensors lack “red edge” bands or bands in the spectral gap between the longer wavelengths associated with visible red and shorter wavelengths of near infrared light; therefore, the NDCI algorithm could not be applied. Chlorophyll-a, however, was used by implementing a proxy for NDCI discussed in the next section.

*3.2.4 NDVI*

Since Landsat satellites and sensors do not have the “red edge” bands necessary to calculate NDCI and Chl-a appropriately, we instead calculated the Normalized Difference Vegetation Index (NDVI) for Landsat imagery to act as a proxy for NDCI. NDVI has been proven to accurately work as a NDCI proxy especially in low Chl-a environments (Buma & Lee, 2020; Boucher et. al, 2018). NDVI *(Equation 5)* yields similar results to NDCI with upper and lower reflectance bounds of +1 and -1:

(5)

*3.2.4 CDOM*

Colored Dissolved Organic Material (CDOM) measures the concentration of suspended organic material in the water column. Higher CDOM indicates increased levels of nitrogen and carbon-based materials, often associated with sewage and agriculture by-products, algal blooms, and in some cases sedimentary material that accumulates on the seafloor, such as material brought up by dredging. We utilized the CDOM algorithm developed by the Chen et al. 2017 paper to calculate the CDOM from 2000 to 2020 using both our Sentinel-2 image collection (*Equation 6*) and the Landsat image collection *(Equation 7):*

(6)

(7)

In this formula, X is the ratio of remote sensing reflectance values between the green and red band, and the coefficient values 22.283 and -1.72 are predetermined for Sentinel-2, and values 45.75 and -2.463 are predetermined values for Landsat based on the Chen et al. 2017 paper. The output of this algorithm is measured in milligram per cubic meter (mg/m3).

*3.2.5 Kd(490)*

Diffuse Attenuation Coefficient of Downwelling irradiance, or Kd(490), indicates the amount of light penetration through the water, which in turn affects the photosynthesis needed for coral health and development. The algorithm, developed by the NASA Goddard Spaceflight Center, is used to calculate Kd(490) through a fourth-order polynomial which utilizes the empirical relationship between the ratio of in-situ data and remote sensing reflectance of blue-to-green bands, and K bio. This parameter was only calculated for Landsat data, for temporal continuity. The coefficient is a ratio between 0 and 1 *(Equation 6)*.

(6)

In this formula, the ratio within the inner set of parenthesis reflects the ratio between the blue and green band reflectance, which are then multiplied and set to the power of each corresponding ‘a’ coefficient across the polynomial. The Kd(490) algorithm was only performed on the Landsat collection for sake of continuity and consistency.

***3.3 Data Analysis***

Satellite imagery data from Sentinel-2 was cross-validated with *in situ* data provided by USACE and NOAA partners. The datasets, collected as raw data through independent monitoring efforts, included water quality information about turbidity and temperature for the different monitoring stations as seen in Figure 2. The GPS coordinate locations of these stations and their respective names are seen in Figure 3. Data collected from monitoring stations WC-4 and WC-6 were used for cross-validation from early December to late January due to time constraints and corrected data availability. Daily average values were calculated for the *in situ* data. The comparison of measurements between the *in situ* data and remotely sensed data allowed our team to identify any similar trends across the data used for the scope of this project. These results helped determine the validity of our tool.

Table

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*Figure 3.* GPS coordinates of each of the monitoring stations,

which correspond to the stars in *Figure 2.*

*Figure 2.* Location of water quality monitoring field stations off the coast of Port Everglades in Florida. (Basemap: ESRI “Light Grey Canvas” & “Satellite Imagery” Layer Package, GARMIN, State of Florida, HERE, ArcGIS Pro).

*3.3.3 Validation and Statistical Analysis*

Satellite data (n=8) was extracted from the SHARQ tool and compared to the *in situ* data (n=8) in the same locations. This dataset was processed using Excel. Linear regression (R2) and root mean square error (RMSE) statistical metrics were used to determine the agreement between water quality output variables along with percent difference (*Equations 10, 11, and 12*).

(10)

(11)

(12)

RMSE is essentially the standard deviation of the residuals (prediction errors) from the line of best fit. The line of best fit is the regression line calculated from a linear regression analysis. Percent error is an expression of the difference between a measured value and the known or accepted value. We calculated the average percent error of our satellite data (the experimental value) and the *in situ* data (the expected values). These metrics are useful in understanding agreement between these values.

# 4. Results & Discussion

***4.1 Analysis of Results***

*4.1.1 Time Series Analysis*

Ultimately, we performed a time series analysis over 20 years, September 2000-September 2020, to establish a baseline average of multiple water quality parameters (turbidity, Chlorophyll-a, CDOM, and Kd(490)) with relative accuracy. Chlorophyll-a and NDCI were only able to be averaged across a 3-year time period using Sentinel-2 imagery from September 2017-2020 (see Methodology for explanation). Though there was a discrepancy between cloud disruption and sensor calibration validation, what can be observed are longer-term patterns and trends, allowing the end user to identify extreme events and anomalies that may be caused by human activities or extreme weather. In the time series chart generated from both our Landsat data (Landsat 5 TM, 7 ETM+, and 8 OLI) and Sentinel-2 MSI data (*Figures 4,5,6*), the water quality parameters were calculated using each respective algorithm discussed in *Section 3.2* of this paper.

*Figure 4*. Turbidity time series analysis for Landsat 5,7,8 and Sentinel-2 (2000-2017). Fluctuation in the charts indicates how turbidity changes based on the season, higher in the summer (more rain) and lower in the winter (less rain). The peaks in the Sentinel-2 graph is likely a result of cloud masking errors.

The turbidity baseline values were calculated using both Landsat and Sentinel-2 image collections. Though both utilized the same algorithm described by Nechad, Ruddick, & Neukermans (2009), the two data collections returned slightly different baseline results. The Landsat collection returned a baseline value of 6.80 FNUs while the Sentinel-2 collection returned a baseline value of 4.34 FNUs. These two values, though slightly different, provided the project partners with an estimated historic baseline that can be used to compare against once the harbor deepening project begins in 2022. One possible cause for this discrepancy could be mixed pixels in our data. Because Landsat’s spatial resolution is coarser than that of Sentinel-2, more area of water is being averaged. The most likely reason for the difference in baseline values is errors in Sentinel-2 cloud masking processing, seen as the outlying peaks in the Turbidity Analysis – Landsat 8 & Sentinel-2 (2017-2020) chart in *Figure 4.* Further discussion of possible errors and uncertainties that may be the cause of the two different baseline values are further discussed in *Section 4.2*.

In all the parameters, seasonality is seen quite clearly. Peaks and troughs are seen from year to year, most likely associated with the yearly wet season cycle. As precipitation occurs, more sediment and nutrients are brought down through the Stranahan river into the Port and then washed out to sea. These slow rises and falls can be identified across all sensors, and across the entire date range.

The Chl-a timeseries charts (*Figure 5*), generated using the Mishra & Mishra 2012 algorithm on the Sentinel-2 collection, returned a baseline value of 7.126. This value can be utilized to establish feasible thresholds that monitoring programs can compare too to judge what could be considered hazardous water conditions during periods of dredging.



*Figure 5*. Chlorophyll-a time series analysis for Sentinel-2 (2017-2020). Fluctuation in the chart indicates how turbidity changes based on the season, higher in the summer (more rain) and lower in the winter (less rain). The peaks in the Sentinel-2 graph is likely a result of cloud masking errors.

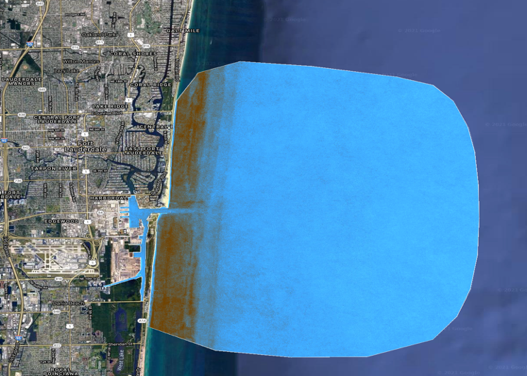
Kd(490) time series charts (*Figure 6*) were generated for the Landsat collection using the algorithm developed by the NASA Goddard Spaceflight Center. The baseline value calculated for Kd(490) was 0.114 m-1. The Kd(490) chart illustrates the seasonality of the Kd(490) values. Dips in the time series occur in the winter months while peaks in the time series occur in the summer months.



*Figure 6.* Kd(490) time series analysis for Landsat 5,7,8 (2000-2020). Fluctuation in the chart indicates how light attenuation change across seasons, higher in the summer and lower in the winter.

*4.1.2 Indices Imagery*

In addition to establishing baseline values using time series analysis, we used output maps to analyze changes in water quality parameters. *Figure 7A* and *Figure 7B* were generated from the Sentinel-2 data and Landsat data, respectively, using the NDTI algorithm by Lacaux et. al (2007). The highest values of turbidity are dark brown, and the lowest values of turbidity are blue. The similarity between the Sentinel-2 and Landsat NDTI map outputs shows how closely the results of the two satellites are. The influence of cloud artifacts and masking disturbances is also something noticeable in these figures. Figure *7A* shows very little disturbance from clouds, the result of refined cloud masking and composite imaging. Figure *7B*, however, does not utilize the same cloud masking technique, and thus contains much more cloud ‘noise’ that can affect not only the image but the values associated.

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B

A

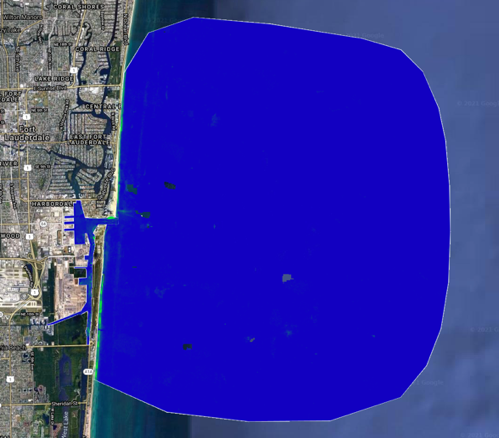
*Figure 7.* NDTI image output Landsat 8 [B] and Sentinel-2 [A], 2019-04-01 to 2019-06-01. The brown color is indicating higher turbidity while the blue color indicates less turbid water.

In *Figure 8C*, which was produced using Sentinel-2 data and derived from the Mishra and Mishra NDCI equation, areas of high Chl-a concentration are shown in green, and areas of low Chl-a concentration are shown in blue. In *Figure 8D*, which was generated from the Landsat collection and used the NDVI algorithm as a Landsat proxy for NDCI, the highest values of Chl-a are illustrated in green. The slight similarity between *Figure 8A and 8B* shows the potential for using NDVI to estimate NDCI for Landsat; however, it is clear more study needs to be conducted on this algorithm.

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C

D

*Figure 8.* NDCI image output Landsat 8 [D] and Sentinel-2 [C], 2019-04-01 to 2019-06-01. The similar colors represents the potential for using NDVI to estimate NDCI with Landsat imagery.

*4.1.3 SHARQ Tool Features*

The SHARQ tool contains many analytical features, including the main feature which visualizes selected water quality parameters based on user-specified study areas and date ranges. When the True Color option is selected, the tool displays the least cloudy image from the image collection that has been filtered by date and area. When the Sea Surface Temperature option is selected, the tool will display the information contained in the sea surface temperature band of the MODIS data. For all other water quality parameters, the median of each pixel location in every image in the image collection will be calculated and then displayed as a composite image. If the user-specified start date is before 2015, Landsat data will be used for parameters that have functions for both Landsat and Sentinel. To receive a visual display based on Sentinel data, the start date must be in 2015 or later.

The time series chart generator is another analytical feature that uses a specified parameter, time range, and study area to create a line graph of the parameter values. Like the time series chart generator, the Point Inspector Tool creates a time series analysis chart based on a user-specified parameter and date. However, the Point Inspector Tool allows the user to specify a single point as the area input to generate the chart. The Slide Viewer feature of the SHARQ tool allows the user to compare two sets of data at the same location. Each side of the slide viewer allows the user to specify a water quality parameter and date range.

*4.1.4 Validation Analysis*

We first performed a linear regression analysis to understand relationships between the satellite data and the limited *in situ* data. *Figures 9-12* show results from this analysis with and without the identified outliers highlighted in *Table A1* of the Appendix. For station WC-4 we can see that the R2 is 0.6372 with the outliers while the R2 without outliers is 0.0019. The closer the R2 value is to 1, the stronger the agreement between the datasets and the better the linear regression model fits our data. However, while the R2 value is closer to 1 for station WC-4, we can see an influence from the outlier that may not be accurate.

*Figure 9 and 10.* Linear regression analysis for water quality monitoring station WC-4. The influence of outliers can be seen in the change of R2 values in these graphs.

*Figure 11 and 12.* Linear regression analysis for water quality monitoring station WC-6. The influence of outliers can be seen in the change of R2 values through these graphs.

For station WC-6, we see an R2 value of 0.1099 with outliers and an R2 value of 0.6706 without the previously identified outliers. Similarly to station WC-4, we see an influence from the identified outliers in the linear regression analysis along with a better agreement between the datasets once the outliers have been removed. We analyzed these relationships further by calculating the RMSE. The lower the RMSE the more concentrated the data is around the line of best fit (linear regression model). As seen in Table 3, there is a difference in RMSE values between non-corrected (dataset that includes outliers) and corrected (without outliers) datasets for both monitoring stations.

Table 3.

*RMSE for monitoring stations WC-4 and WC-6 with non-corrected and corrected values. The influence of non-corrected values can be seen here.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dataset | Non-corrected WC-4 data vs. Sentinel-2 imagery | Corrected WC-4 data vs. Sentinel-2 imagery | Non-corrected WC-6 data vs. Sentinel-2 imagery | Corrected WC-6 data vs. Sentinel-2 imagery |
| RMSE | 37.82 | 0.58 | 36.06 | 0.32 |

Percent error values were also taken between the remotely sensed data and *in situ* measurements and are seen in table A2 and table A3 of the Appendix. These measurements represent the difference between average satellite values (our experimental value) and *in situ* values (our expected values), divided by the average *in situ* values. These data do not include the outliers previously highlighted and extracted from our analysis. The resulting percent difference for station WC-4 was 1% indicating the satellite data was on average within 1% difference of the *in situ* data. The resulting percent difference for station WC-6 was 12% indicating the satellite data on average was within 12% difference of the *in situ* data.

From these analyses we can see that there is some agreement among satellite and *in situ* data however, further analysis should be done in future work using a larger dataset to establish a stronger confidence interval. In addition to this, future comparisons should take note of major events that could cause spikes (outliers) in the dataset such as faulty sensors, runoff events, storms, or cloud masking.

***4.2 Errors and Uncertainties***

Drawing conclusions on water quality trends from satellite imagery data is difficult due to the complexity of each parameter and inherent limitations in measuring them remotely. The predominant challenge that prevents us from being confident in our conclusions is caused by inconsistencies between sensors, specifically with varying spectral resolutions across the sensors used. A visual analysis of the time series chart (*Figure 4*) shows the inconsistency of values between sensors. While the remotely sensed values outputted from the SHARQ tool were cross validated with *in situ* data collected within our area of study, only a limited amount of *in situ* data was available for our study purposes. The *in situ* data we had access to was a very limited subset of a large, uncorrected dataset, restricting the extent of our cross-validation analysis. Our project’s study period is relatively long, leaving additional room for uncertainties given the use of multiple sensors and having temporally limited *in situ* data (>1 month of measurements). The RMSE values from the cross-validation indicate a need for algorithms that are better calibrated and better suited to the project’s study area and chosen sensors. However, it is important to note that the limited amount of *in situ* data we had access to is not enough to confidently conclude accuracy of the entire SHARQ tool, as the dates of the *in situ* data only overlaps with Sentinel-2 data, which we have identified as being prone to error.

Additionally, the study area used for the creation of the time series is the tool’s default study area which encompasses the port, near shore, and open ocean areas. The water quality characteristics of these three environments are vastly different. For example, turbidity is usually much higher in the port area than in the open ocean. By using the extent of the default study area, the parameter values of these vastly different environments are averaged and, as a result, do not accurately represent the real-world conditions of any of the three environments. Using a more specific and homogenous study area would increase confidence in the results.

Cloud-masking and atmospheric correction of the satellite imagery used also introduces another source of error since results are dependent on the algorithms and study area used. Even after cloud masking efforts, there were still lingering residual clouds that distort reflectance values, leading to potentially inaccurate algorithm results, especially in the case of Sentinel-2 data. The atmospheric correction of Landsat 5, 7, and 8 imagery data was already completed by the United States Geological Survey prior to download and after download, we applied a cloud mask. However, Sentinel-2 imagery was corrected using the MAIN algorithm after downloading the data. This difference in correction methods, and our limited understanding of the MAIN algorithm, introduce the opportunity for error. Even after applying these corrections, residual clouds remain that distort reflectance values and result in potentially inaccurate algorithm results.

Algorithm calibration and selection also bring uncertainty into the validity of the SHARQ tool’s outputs. These algorithms are generally calibrated to the type of sensor and characteristics of the study area using coefficients determined based on *in situ* data. With no access to such *in situ* data, we instead used calibrations based on those used in similar study areas and contexts, such as the MAIN algorithm for Sentinel-2 data. This data provided limited turbidity value outputs due to outliers most likely caused by faulty or insufficient cloud removal from the atmospheric correction process. Given less than ten weeks to work on this project, a limited amount of time was allotted towards researching the chosen algorithms. With additional time, more research could be completed to find and select algorithms better suited for analysis needs.

***4.2 Future Work***

Given more time, our team would focus on expanding our analyses to further develop the SHARQ tool’s capabilities and potential applications. Additional time would be used to add more water quality parameters to the tool, such as salinity, which could provide insight on potential additional stress to corals during periods of increased turbidity. The current water quality algorithms would be reviewed and replaced with better-suited algorithms when necessary. Our team also envisions the development of greater functionality within the SHARQ tool’s graphical user interface. One potential idea is adding a feature that allows users to export imagery into easily accessible digital formats such as portable network graphics (PNG) or JPEGs.

The availability of more corrected *in situ* data would also improve the accuracy of the outputs of the SHARQ tool. In the future, more data will be available and could be used for better calibration and further validation. Lastly, our team discussed how extreme weather events such as hurricanes should also be considered in the future. Hurricanes may contribute to turbidity disruptions, but also restrict the ability of satellite imagery analysis to pick up on such events due to increased cloud cover associated with these types of storms. Going forward, further investigation into the SHARQ tool’s ability to identify extreme weather events is necessary.

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# 5. Conclusions

Utilizing satellite imagery for water quality monitoring provides research capabilities that complement and enhance *in situ* sampling research methods. Using these resources, our team was able to develop the Seaport & Harbor Area Resource Quality (SHARQ) tool using Google Earth Engine and its library of satellite imagery, allowing end-users to analyze water quality parameters both spatially and temporally. With remotely sensed data, the tool extracts parameter measurements using regular and consistent observations for large areas, which would otherwise be costly and difficult to achieve with *in situ* observations alone.

The SHARQ tool produces a historical baseline of water quality parameters which can be used by the end-users to assist in the establishment of thresholds for healthy vs. dangerous levels of turbidity during periods of dredging and public works. This not only advances the ability to balance the cost and benefit of such a large-scale project, such as the Port Everglades harbor deepening, but also makes large strides in the ability to protect the nearshore reef ecosystems from turbidity events in general. With different sources of data available, more informed mitigation decisions can be implemented regarding future dredging projects. Those databanks can also be used to help inform higher-level conservation policy (i.e. state-level standards and thresholds, state conservation department techniques, etc.).

Our project partners, the USACE and NOAA National Marine Fisheries Services, can use the SHARQ tool to extract historical baseline values for several water quality parameters. Such info will serve as a basis of comparison that can be used to effectively assess the potential impacts of the future harbor dredging project on the Florida Reef Tract. The outputs of the SHARQ tool will allow our partners to measure important water quality parameters remotely and across time, supporting them in making data-driven decisions for future monitoring and mitigation efforts.

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# 7. Glossary

**CDOM**: Colored Dissolved Organic Material

**Chlorophyll-a**: Photosynthetic pigment found in chloroplasts of plants, algae, and plankton

**Earth observations**: Satellites and sensors that collect information about the Earth’s physical, chemical, and biological systems over space and time

**GEE**: Google Earth Engine

**GUI**: Graphical User Interface

**Kd(490)**: Diffuse Attenuation Coefficient at 490nm

**MAIN**: Modified Atmospheric correction for Inland waters

**MODIS**: Moderate resolution Imaging Spectroradiometer

**MSI**: Multispectral Instrument

**NDCI**: Normalized Difference Chlorophyll Index

**NDTI**: Normalized Difference Turbidity Index

**NOAA**: National Oceanic and Atmospheric Administration

**NMFS**: National Marine Fisheries Service

**OLI**: Operational Land Imager

**ORCAA**: Optical Reef & Coastal Area Assessment

**RMSE**: Root mean square error

**SHARQ**: Seaport & Harbor Area Resource Quality

**SST**: Sea Surface Temperature

**USACE**: United States Army Corps of Engineers

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# 9. Appendix

Table A1*.*

*Linear Regression Results on in situ data with identified outliers highlighted*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Date | Turbidity Station WC-4 Satellite Data (NTU) | Turbidity Station WC-4 *In situ* Data  (FNU) | Turbidity Station WC-6 Satellite Data (NTU) | Turbidity Station WC-6 *In situ* Data  (FNU) |
| 12/6/20 | 1.994 | 1.717 | 2.054 | 1.429 |
| 12/11/20 | 1.998 | 1.663 | 1.548 | 1.448 |
| 12/16/20 | 1.362 | 1.788 | 1.137 | 1.510 |
| 12/31/20 | 2.957 | 109.741 | 1.137 | 103.78 |
| 1/5/21 | 1.178 | 1.641 | 0.915 | 1.449 |
| 1/10/21 | 1.662 | 1.668 | 1.476 | 1.482 |
| 1/15/21 | 1.909 | 1.700 | 1.516 | 1.430 |
| 1/20/21 | 1.215 | 7.669 |  |  |

Table A2*.*

*Percent error values between remotely sensed data and WC-4 in situ measurements*

|  |  |  |  |
| --- | --- | --- | --- |
| Date | Normalized  WC-4 (satellite) | Normalized WC-4 (*in situ)* | Normalized Percent Difference |
| 6-Dec-20 | 1.994 | 1.716689 | 16% |
| 11-Dec-20 | 1.998 | 1.663258 | 20% |
| 16-Dec-20 | 1.362 | 1.78810432 | -24% |
| 5-Jan-21 | 1.178 | 1.64067738 | -28% |
| 10-Jan-21 | 1.662 | 1.66768909 | 0% |
| 15-Jan-21 | 1.909 | 1.69991271 | 12% |
|  |  | **Average Difference** | **-1%** |

Table A3.

*Percent error values between remotely sensed data and WC-6 in situ measurements*

|  |  |  |  |
| --- | --- | --- | --- |
| Dates | Normalized WC-6 (satellite) | Normalized WC-6 Top *(in situ)* | Normalized  Percent Difference |
| 6-Dec-20 | 2.054 | 1.42918 | 44% |
| 11-Dec-20 | 1.548 | 1.447803 | 7% |
| 16-Dec-20 | 1.137 | 1.50839 | -25% |
| 21-Dec-20 | 0.339 | 1.588319 | -79% |
| 5-Jan-21 | 0.915 | 1.448723 | -37% |
| 10-Jan-21 | 1.476 | 1.482111 | 0% |
| 15-Jan-21 | 1.516 | 1.429678 | 6% |
|  |  | **Average Difference** | **-12%** |