TRANSFORMATION OF THE NORMALIZED DIFFERENCE CHLOROPHYLL INDEX TO RETRIEVE CHLOROPHYLL-A CONCENTRATIONS IN MANILA BAY

Manuel, A.[1,2], Blanco, A.C.[1,2, 3]

[1]Department of Geodetic Engineering, University of the Philippines Diliman, (amimanuel@gmail.com, acblanco@up.edu.ph)
[2]Training Center for Applied Geodesy and Photogrammetry, University of the Philippines Diliman
[3]Space Information Infrastructure Bureau, Philippine Space Agency, Diliman, Quezon City

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ABSTRACT:

Manila Bay is one of the most significant harbors in the region, enabling commerce and trade between the Philippines and other countries. Its abundant natural resources have provided for generations of its inhabitants and have driven socio-economic development for centuries. Like other water bodies adjacent to highly urbanized cities, the increased organic and nutrient loading from untreated domestic, industrial, and agricultural wastes resulted to further degradation of its water quality. While frequent water quality monitoring is ideal, data from traditional field sampling methods might not be sufficient to assess the spatial and temporal variations of water quality in Manila Bay. Remote sensing fills the need for a frequent and full overview of the bay's water quality. Sentinel-3 images were initially processed through the Case 2 Regional CoastColour (C2RCC) model to retrieve the remote sensing reflectance. The Normalized Difference Chlorophyll Index (NDCI) was computed for the images and were modeled against the C2RCC-derived chlorophyll-a estimates. From this, we were able to get a general equation (TNDCI – transformed NDCI) to retrieve chlorophyll-a concentrations from two reflectance bands (Oa8 and Oa11). TNDCI gave an R^2 of 0.9 and RMSE = 5.12 ug/L as compared to C2RCC values, and an R^2 = 0.85 and RMSE = 2.44 ug/L with field data.

1. INTRODUCTION

1.1 Manila Bay

Manila Bay is regarded as one the most significant harbors in the region, enabling commerce and trade between the Philippines and other countries. It provides countless livelihood opportunities for millions of Filipinos and secures their aquaculture resource needs. With a watershed area of 17,000 km^2, the bay is surrounded by a metropolis and other densely populated coastal areas including those in the provinces of Cavite and Bulacan. Light and heavy industries can be found in other surrounding provinces (e.g., Bataan) and are also dispersed throughout Metro Manila.

For decades, multiple environmental concerns and challenges affect Manila Bay. The increased organic and nutrient loading from untreated municipal, industrial, and agricultural wastes from the watershed result to further degradation of its water quality (Jacinto et al., 2006). With the deteriorating state of the bay, frequent water quality monitoring is ideal (Gray & Shimshack, 2011). The typical number of field sampling points might not be sufficient to assess the spatial and temporal variation of water quality in Manila Bay (Khattab & Merkel, 2014). In addition to field sampling being expensive, collecting data from the entire Manila Bay can be time-consuming due to its size. The weather and sea conditions also make it challenging for most boats and transport vessels to cover greater distances in a single field day. Images taken by multispectral satellite sensors fulfill this need for a frequent view of the water quality in Manila Bay. These can strengthen policy makers' capacity to sufficiently monitor water bodies.

Sentinel-3 OLCI (Ocean and Land Color Instrument) provides excellent potential for remote sensing of water quality by providing imagery with high spectral resolution and practically daily image capture. Since the OLCI was built especially for water management, the number and placement of spectral bands are deliberately placed for retrieval methods of water quality. This study aims to simplify mapping Manila Bay's chlorophyll-a concentrations from Sentinel-3 images using a transformed index.

2. BACKGROUND

2.1 Chlorophyll-a

Phytoplankton are the most prolific primary producers on earth residing in the oceans and lakes. Even though they are microscopic in size, they are of global importance because they produce approximately half of the oxygen that makes our atmosphere breathable (Field et al., 1998). They therefore play a crucial role in sustaining life on Earth and are of keen importance to biologists and scientists who research the biogeochemical cycles of the planet (Matthews, 2017).

Chlorophyll-a is the photosynthetic green pigment found in all photoautotrophic plants and bacteria. It is the primary light-harvesting pigment, responsible for capturing most of the sunlight required for photosynthesis. Chlorophyll-a absorbs light strongly at wavelengths in the blue (near 440 nm) and red (near

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670 nm) regions of the electromagnetic spectrum. This shows the characteristic green hue to natural waters abundant in phytoplankton (Matthews, 2017).

Due to the presence of chlorophyll-a in phytoplankton, including algae and bacteria, and its significant positive relationship with phytoplankton biomass, chlorophyll-a is used worldwide as a proxy for phytoplankton in natural waters (Desortová, 1981). Along with its ease of measurement in the laboratory from field samples, or from direct fluorescence-based measurements, it is consistently measured in water quality monitoring programs by government agencies around the world (Gregor & Maršálek, 2004).

2.2 Water Quality Indices

Estimation of bio-optical parameters such as chlorophyll-a and suspended particulate matter in productive waters have been essential for large-scale and multi-temporal studies of the biogeochemical cycles of inland and coastal water quality. Remote sensing has been proven as a useful tool to map these optically active constituents and overcomes the spatio-temporal limitations of in-situ sampling. Semi-analytical bio-optical models have been used to produce reliable results but has been found to depend on accurate parameterization of inherent optical properties of the water body. This is a challenge considering the intensive field methods and equipment required to measure contributions to the model.

Different water bodies have different optical complexities and uncertainties in absorption of constituents in water are also tied with other factors such as salinity and temperature. The ease of application of remote sensing indices would be beneficial over semi-analytical models particularly for initial evaluation of overall state of water quality in a body of water. These indices are simple yet effective ways to see the changes in characteristics in an area. However, they are designed to be applicable to a wide variety of study areas, and thus can be treated as relative estimates if to be used in smaller regions.

2.3 Normalized Difference Chlorophyll Index

The Normalized Difference Chlorophyll Index (NDCI) was proposed by Mishra and Mishra (2012) to estimate chlorophyll-a concentration from remote sensing data of estuarine and coastal turbid productive waters. Calibration and validation results were derived and simulated with MERIS datasets and showed potential application to a wide variety of water types in different geographic regions.

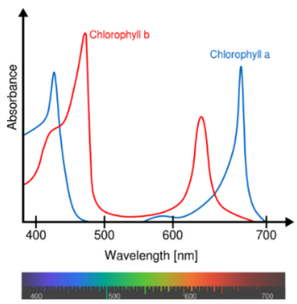

Figure 1. Absorbance spectra for chlorophyll pigments © Daniele Pugliesi and Motty

NDCI makes use of the reflectance values at 665nm and 708nm. Many chlorophyll-a estimation algorithms focus on the absorption peak in 665-675nm and the reflectance peak at 700 nm. These spectral bands also have minimal influence from CDOM and TSS on its reflectance compared to bands at shorter wavelengths. Since these bands are closely located, CDOM and SPM absorption in this range is similar in magnitude and their difference is considered negligible.

$$C_{chl-a} \propto \frac{[R_{rs}(708) - R_{rs}(665)]}{[R_{rs}(708) + R_{rs}(665)]} \tag{1}$$

NDCI was developed by taking the spectral band difference at 708 nm and 665 nm. By normalizing the sum of their reflectance, it eliminates uncertainties brought by seasonal solar azimuth differences and atmospheric contributions at those wavelengths.

NDCI range	*Chl-a range (mg/m³)*
< -0.1	<7.5
-0.1 to 0	7.5-16
0 to 0.1	16-25
0.1 to 0.2	25-33
0.2 to 0.4	33-50
0.4 to -0.5	>50
0.5 to 1	Severe bloom

Table 1. Qualitative comparison between NDCI and chlorophyll-a concentration from study regions

Table 1 shows the qualitative comparison assessed from the different study regions using MERIS images. NDCI range varies between -1 and 1 for areas without cloud contamination. Qualitative chlorophyll-a mapping and bloom detection can be possible and further analysis from local in-situ data can be used to further relate exact chlorophyll-a ranges with NDCI values.

Sentinel 3 OLCI Bands Oa8 and Oa11 with central wavelength at 665 and 708.75 nm, respectively have specific application in retrieving chlorophyll-a. These also match the reflectance bands used in NDCI. Blanco et al. (2020) used the ratio of these two bands and showed strong correlation with total chlorophyll-a concentration in Laguna Lake.

2.4 Transformed NDCI

NDCI has shown good relationship with the chlorophyll-a outputs from C2RCC. As it is ideal for remote sensing indices to make computations as simple as possible, the accuracy of the values must also not be sacrificed. The outputs from NDCI were modeled to the C2RCC outputs so that a simple transformed equation can be applied to Manila Bay.

The resulting model is a localized water quality index (Transformed NDCI) specifically created to measure Manila Bay chlorophyll-a concentrations. The purpose of this study is to estimate chlorophyll-a concentrations from simple computations involving the two spectral bands in NDCI. This shows that chlorophyll-a in Manila Bay can be easily mapped without the calibration and high computational requirements needed by other water quality mapping models.

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3. DATA AND METHODS

3.1 Data

Sentinel 3 OLCI EFR Level 1C products are used as the input images for this study. Images from January 2017 to July 2021 were downloaded from the ESA data products archive. The C2RCC processor (Brockmann et al., 2016) was applied to retrieve both the remote sensing reflectance (R_{rs}) and chlorophyll-a and TSM estimates from the L1C products.

Chlorophyll-a concentrations from a spectrofluorometer used in a field survey from 27 May 2021 was also used for the validation of the generated model.

3.2 Methodology

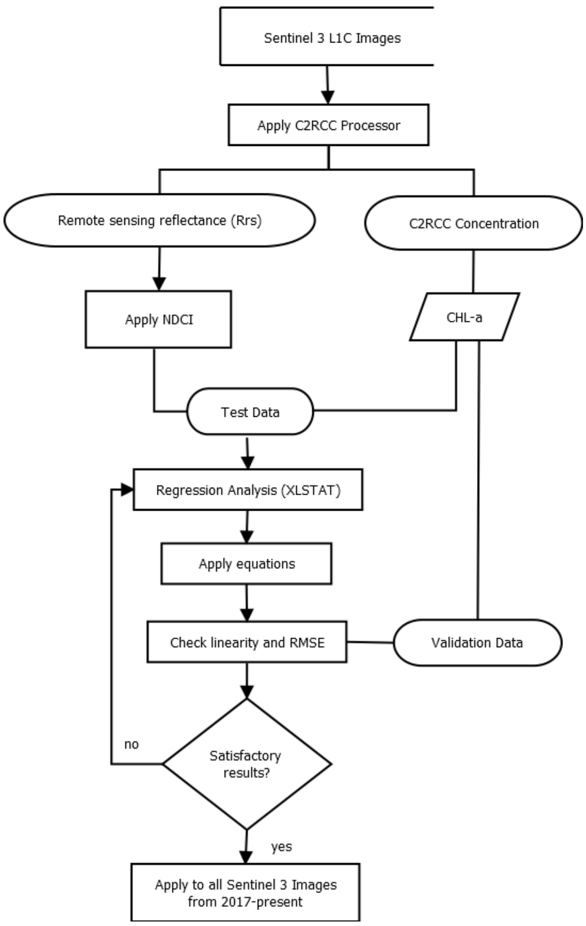

Figure 2. Workflow for development and application of the transformed NDCI

Figure 2 shows the general workflow done to produce chlorophyll-a maps from Sentinel 3 images and the transformed index. As mentioned above, the C2RCC Processor was first applied to all the available Sentinel 3 L1C images. These outputs both the remote sensing reflectance and chlorophyll-a concentrations. NDCI was applied to the reflectance images and the output water quality estimates was checked for linearity with the C2RCC-derived chlorophyll-a products. Regression analysis was then done through XLSTAT, an MS Excel add-in, to model the index to the C2RCC water quality outputs.

Through regression analysis, we were able to generate an equation that can be applicable to the whole Manila Bay and give accurate estimates for chlorophyll-a and turbidity. This was done by taking a random 10% sample for 12 Sentinel-3 images in 2020. One cloudless image for each month from 2020 were used to model an equation from NDCI to C2RCC Chlorophyll-a outputs, resulting to a total of 52744 points. In the first modeling iterations with test images, we found out that the relationship between NDCI values and chlorophyll-a concentrations were best explained by an exponential model. Non-linear regression was chosen to model the NDCI values and the C2RCC concentrations.

4. RESULTS AND DISCUSSION

4.1 Non-linear Regression

The regression analysis was carried out with XLSTAT. Table 2 shows the goodness of fit statistics for the non-linear regression of C2RCC-derived chlorophyll-a and NDCI.

STATISTIC	FULL
Observations	52744.000
DF	52742.000
SSE	1385644.705
MSE	26.272
RMSE	**5.126**
AIC	172398.223
AICC	172398.223
Iterations	17.000

Table 2. Summary statistics table for modeled NDCI Chlorophyll-a

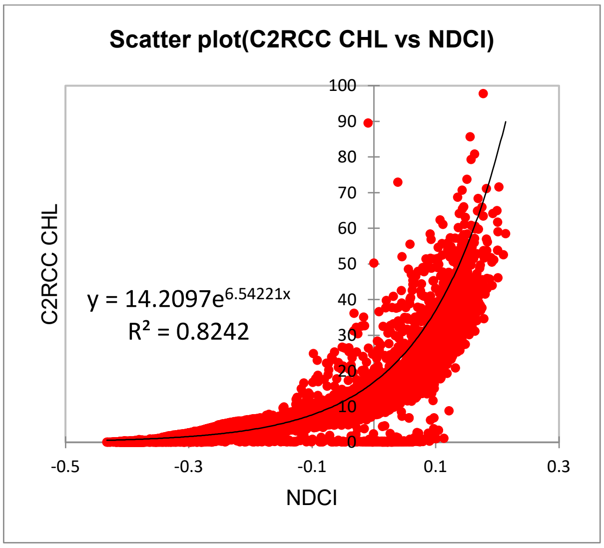

Figure 3. Scatterplot for the sample NDCI values and C2RCC-derived chlorophyll-a concentrations

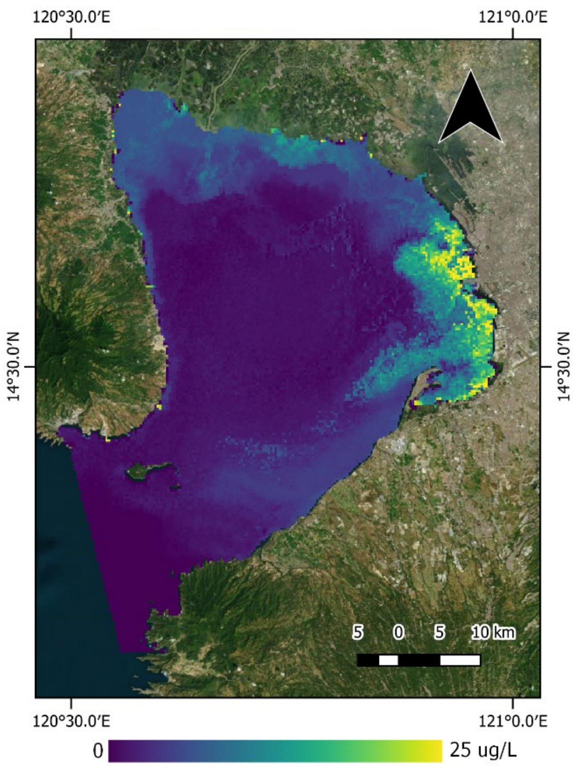

Figure 4. C2RCC Chlorophyll-a (March 29, 2020)

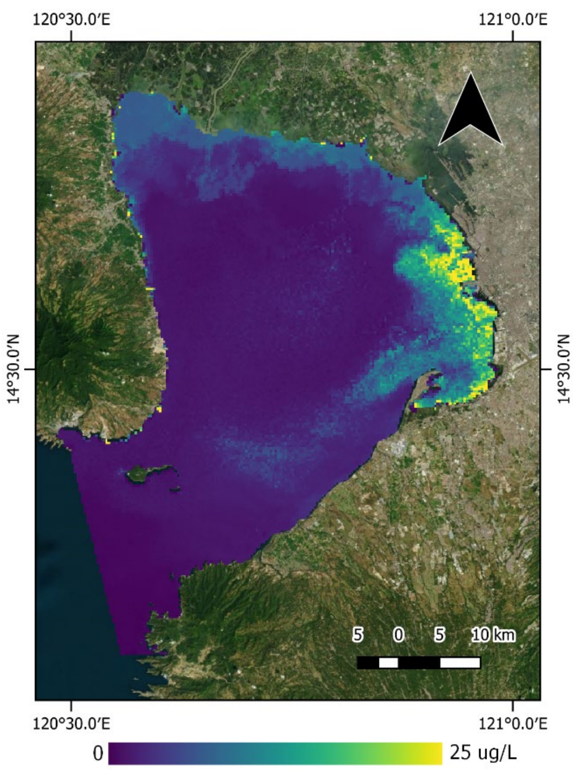

Figure 5. TNDCI Chlorophyll-a (March 29, 2020)

Figure 3 shows the scatterplot for the sample NDCI values and C2RCC-derived chlorophyll-a concentrations, displaying an exponential growth model. Equation 2 shows the calculated best fit exponential model for estimating chlorophyll-a in Manila Bay which we called the Transformed NDCI or TNDCI.

$$TNDCI = 14.2097 * \exp(6.4221 * NDCI) \qquad (2)$$

Figures 4 and 5 show the comparison of the two chlorophyll-a concentrations for the date 29 March 2020. We can see similar areas of high and low chlorophyll-a concentrations from the two outputs. This image from 29 March 2020 is considered part of the peak dry season in the country. Both figures show that chlorophyll-a concentrations in the east side of the bay (Metro Manila) is higher than in the areas up north (Pampanga and Bulacan) for this date, and the lowest concentrations on the mouth of the bay opening to the open seas.

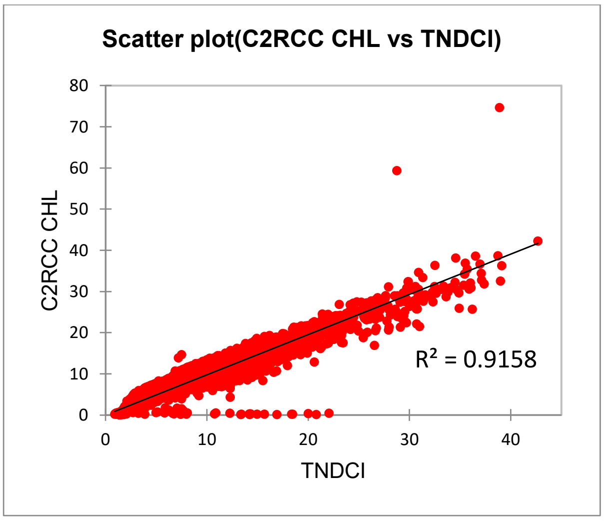

Figure 6. Scatterplot between C2RCC chlorophyll-a and TNDCI values for 29 March 2020 image

Figure 6 shows the strong linear correlation between C2RCC chlorophyll-a concentrations and the transformed NDCI outputs. The resulting R^2 is 0.9158 and its RMSE is at 1.26 ug/L.

4.2 Comparison with Field Data

TNDCI has shown linearity with the C2RCC outputs. Figure 7 shows how they perform when compared against field survey data. TNDCI from 27 May 2021 was used as there was a concurrent in-situ data samples taken during that date. TNDCI and total chlorophyll-a concentration data from the submersible spectrofluorometer has an R^2 of 0.8515 and an RMSE of 2.44 ug/L.

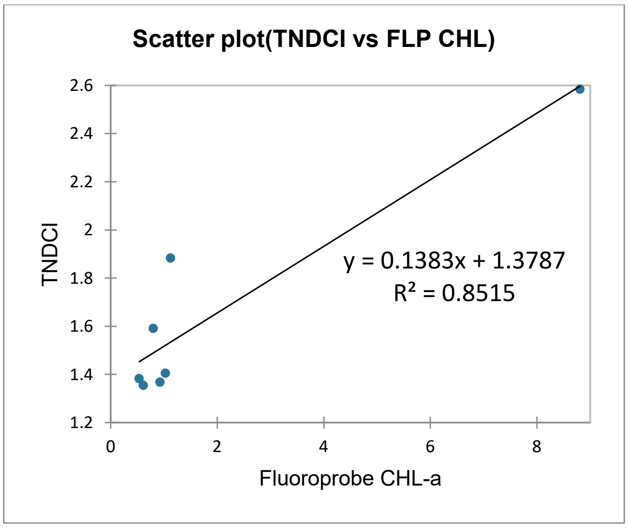

Figure 7. Scatterplot for TNDCI and Fluoroprobe chlorophyll-a concentrations

5. CONCLUSION

A localized water quality index for Manila Bay was developed from the Normalized Difference Chlorophyll Index (NDCI). These were modeled with C2RCC chlorophyll-a to produce what we called Transformed NDCI (TNDCI), which can easily and simply estimate chlorophyll-a of Manila Bay from only two spectral bands and is not as computationally intensive as semi-analytical models. TNDCI yielded an R^2 of 0.9 and RMSE = 5.126 ug/L as compared to C2RCC values, and an $R^{2=}$ 0.85 and RMSE = 2.44 ug/L from field data. The transformed index for Manila Bay was applied to a total of 336 Sentinel-3 images from the years 2017-2021.

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