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Spatial Variability Assessment on The High-resolution Chlorophyll-a Extraction from Landsat 8 and Sentinel 2 Imageries in Johor Waters

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Abstract - **High resolution Chlorophyll-a (Chl-a) can indicate the trophic status of the water and provide useful information on optical features of water body in water quality monitoring. Remote sensing has great potential to offer the spatial and temporal coverage needed. Over the last decades the SeaWIFS and MODIS were applied, but not suitable due to the low spatial resolution for monitoring Chl-a in coastal area. However, the retrieval of Chl-a in the coastal region is usually challenging due to the other in-water substances regardless of Chl-a, hence resulting in the satellite retrieved Chl-a overestimation. By the advancement of the Sentinel-2 and Landsat 8 satellites, continuous high resolution optical imageries have served for remarkable coastal mapping capability thanks to the spectroscopic capability certain spectral bands and as high as 10-meter spatial resolution. This paper aims to evaluate the performance of the SEADASS and SNAP processor for Chl-a estimation from the Operational Land Imager (OLI) and MultiSpectral Instrument (MSI) data in Johor waters. The representative models, in standard algorithm OC3 and C2RCC, were adapted to retrieve Chl-a concentration. The statistical regression has shown that these algorithms give an acceptable Chl-a estimation at medium and high resolution with $R^2 = 0.44$ from OC3 and $R^2 = 0.55$ from C2RCC comparing to the in-situ data. Despite of the spatial, temporal and spectral variability, this paper shows that OLI and MSI could provide Chl-a mapping capability at suitable Chl-a estimation techniques.**

Keywords— Chlorophyll-a, remote sensing, spatial resolution, band ratio.

I. Introduction

Chlorophyll-a (Chl-a) concentration plays an important role as an indicator for biomass and abundant of phytoplankton in the ecosystem [1, 2]. Conventionally, in situ measurement has been practiced for measuring the Chl-a concentration. Yet, such acquisition limit to provide historical and long-term information and this becomes even more complicated for larger Chl-a mapping campaign.

Optical remote sensing has made a significant impact and proved to be useful in Chl-a mapping. Water containing marine biotic features has more complex characteristics, as the organisms contain chlorophyll and other pigments used for photosynthesis. Photosynthetic pigments absorb sunlight strongly and record peaks at different wavelengths of absorption spectrum [3]. Since 1978, several sensors have been designed for ocean colour observation and commonly used to study marine biotic populations. Ocean colour satellite instruments, such as the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) and the Moderate Resolution Imaging Spectroradiometer (MODIS), are widely used by oceanographers in which comprehensive data on the near-surface concentration of the photosynthetic pigment, spatio-temporal Chl-a (mg m^{-3}) can be extracted [4]. However, these sensors only satisfy the basic requirements for measuring Chl-a in open ocean. For Case-2 water, the requirement of higher spatial resolution is high to provide less than 1 km Chl-a mapping for estuaries and coastal waters.

Case-2 water conditions typically occur in coastal water where the optical properties are significantly influenced by the other constituents, such as dissolved organic materials (DOM or CDOM) and suspended particulate materials whose concentration do not covary with the phytoplankton concentration. High resolution Chl-a can indicate the trophic

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status of the water and provide useful information on optical features of water body that is usually applicable to water quality monitoring and phytoplankton study. With the development of remote sensing techniques, the spectral resolution of the satellite data has been improved [5]. MSI and OLI have served for continuous high and medium resolution optical imageries and embarked remarkable Chl-a mapping capability and observation of coastal water in finer details thanks to the multispectral images with spatial resolution of 10 and 30 meters and revisit interval of 10 to 16 days respectively.

Historically, algorithm based on a spectral ratio of remote sensing reflectance (*Rrs*) has been used to produce global Chl-a product from measurements made by satellite instruments. The accuracy and utility of an empirical ocean colour algorithm for estimating global Chl-a distributions depends on the characteristics of the algorithm and the in-situ observations [6]. NASA has provided a few standard Chl-a algorithm such as OC4 and OC3M for SeaWiFS and MODIS sensors. OC4 sensor has four spectral channels covering blue to green bands at 443, 490, 510 and 555 nm. For OC3M, two spectral channels from blue to green range (443, 488 and 547 nm). However, this refinement is confined to Case-1 water (e.g clear water) [7]. OC3L algorithms combine two algorithms, the band ratio OCx algorithm and the Hu color index (CI) algorithm to estimate the Chl-a concentration. The OCx algorithm is a fourth-order polynomial relationship between a ratio of *Rrs* and Chl-a in situ and the CI algorithm is a three-band reflectance difference algorithm employing the difference between *Rrs* in the green band and a reference formed linearly between *Rrs* in the blue and red bands, with a sensor-specific coefficients, a_0 to a_4. C2RCC processor is composed of a set of additional neural networks performing specific tasks and special neural networks have been trained to cover extreme ranges of scattering and absorption. The models provide a robust, fast and easy to implement approaches in estimating bio-optical constituents by also taking into consideration the highly turbid and eutrophic waters where the conventional bio-optical models usually failed.

In the Case-2 water, the retrieval of Chl-a is usually challenging due to low spatial resolution for monitoring Chl-a in coastal region and other in-water substances regardless of Chl-a, hence resulting in satellite-retrieved Chl-a overestimation. Previous study has reported a highly overestimated Chl-a retrieved using NASA standard algorithm was found in the Case-2 water of Malacca Straits due to high nutrient inputs discharged from the rivers [8-9]. The study on the overestimation of Chl-a in Case-2 water also supported by Sun [10], Cannizarro [11], Moses [12] and Darecki [13] at different regions.

Less study was conducted to study the Chl-a estimation by using remote sensing in Johor water. Therefore, this paper aims to evaluate the derivation of Chl-a concentration from OLI and MSI using standard algorithm, OC3L and C2RCC. The performance of both algorithms was validated using in situ measurement to the specific conditions of Johor water. Consequently, the statistical analysis presents the performance and the suitability of both algorithms in retrieving Chl-a from Case-2 water.

II. MATERIALS AND METHODS

A. Study Area

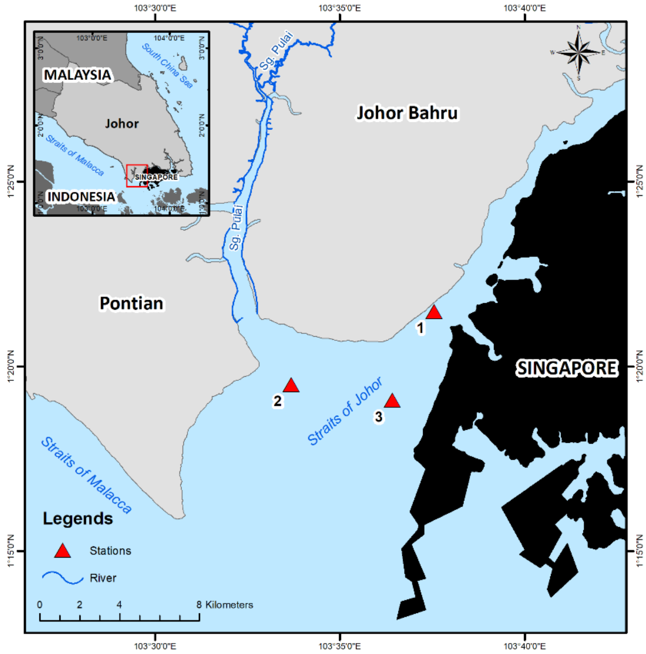

Fig. 1. The study area in the West Johor Straits. The red triangle marks the sampling points where the in-situ measurements were collected.

The study area located at West Johor Straits in the southeast coast of Peninsular Malaysia (1° 10' 0" N – 1° 30' 0" N and 103° 20' 0" E – 103° 40' 0" E). It receives freshwater inflows and exposed to nutrients expelled from numerous rivers (i.e. Sg. Pulai) and subjected to tidal influence by the Straits of Malacca and Straits of Johor. The West Johor Straits also experiences a tropical climate and primarily subjected to two monsoon seasons - the Northeast Monsoon (NEM) and the Southeast Monsoon (SEM) [14]. In the eastern Malacca Straits, high concentrations of Chl-a are likely occurring due to the upwellings resulted by the NEM. During the SEM, the prevailing wind suggested the cause of downwelling that resulted in low concentrations of Chl-a. The whole area has experienced rapid industrialization and urbanization and has adversely impacted the water quality of Johor water. Station 1 is located near to Forest City, station 2 closely to Port of Tanjung Pelepas and Station 3 is very near to Pulau Merambong. Figure 1 shows the map of study area.

B. In Situ Measurement

Phytoplankton samples were collected fortnightly during high tide from January 2017 to December 2018. Triplicates of 1-L water samples were collected at subsurface water using a Van Dorn water sampler for dissolved inorganic and Chl-a analysis. For the Chl-a analysis, 1-liter seawater samples were filtered onto glass-fibre filters (Whatman®, UK). The filters were blotted dry, folded in aluminium foil, and kept frozen prior to Chl-a extraction. Chl-a was extracted by 90 % acetone; and measured by using the multi-wavelengths spectrophotometer as described in Parsons *et al.* (1984).

The concentration of Chl-a (mg m^{-3}) was estimated by using the following equation

$$\mathrm{Chla} = \frac{(11.85\ \mathrm{E}\ 664\ -\ 1.54\ \mathrm{E}\ 647\ -\ 0.08\ \mathrm{E}\ 630\ )\mathrm{x}\ \mathrm{v}}{V\ \times 1} \quad (1)$$

where, *E* represents the absorbance at different wavelength (corrected by 750 nm reading), *v* is the volume of acetone (ml), *V* is the volume of water filtered (liter) and *1* is the path length of cuvette (cm).

C. Satellite Data

To meet the requirements of ocean colour remote sensing, the medium and high resolution satellite data, Landsat 8 OLI and Sentinel-2 MSI were employed in this study. OLI imagery can generate high-quality aquatic science products, such as remote sensing reflectance (*Rrs*) with high spatial resolution, up to 30 meters that allow Chl-a mapping and monitoring optical properties of inland waters, with 11 spectral bands channel in the visible/near infrared (VNIR), short wave infrared spectral range (SWIR), panchromatic, cirrus and thermal infrared zone. However, the revisiting time of 16 days has slightly restricted the capability to monitor coastal water conditions in Johor waters. The launched of the twin satellites of Sentinel-2 MultiSpectral Instruments (MSI), S2A in 2015 and S2B in 2017, respectively, has improved the temporal resolution of satellite data. These data were selected due to it spatial resolution of 10-m and a 10-day revisit period for each single Sentinel-2 and 5-days revisit period for the combined constellation over the study area. Level-1C data with 13 spectral channels in the visible, VNIR and SWIR were obtained from https://scihub.copernicus.eu/ for further Chl-a analysis.

The time gap between the satellite and in-situ data were calculated to match up with in situ data, up to 5 days apart. The *Rrs* were extracted using OC3L and neural network and validated with the in-situ data.

D. Chl-a Derivation

The empirical Landsat OC3L algorithm is devised in the basis of band ratio, *Rrs* at 443, 482, 561 and 655 nm. The Chl-a algorithms combine two algorithms, OC3 band ratio algorithm and Hu color index (CI) algorithm (Chl-hu) [15]. The CI algorithm is used for chlorophyll retrievals below 0.15 mg m^{-3}. For chlorophyll retrievals above 0.2 mg m^{-3}, the OC3 algorithm is used. Meanwhile, if the values in between 0.15 mg m^{-3} and 0.2 mg m^{-3}, the CI and OC3 algorithm are blended using a weighted approach.

Several inputs including *Rrs* band ratio and the global coefficients, a_0 to a_5 were employed in empirical algorithm to estimate the chlorophyll-a concentration. Spectral remote sensing reflectance, *Rrs*(λ) were expressed by the spectral radiance upwelling from beneath the ocean surface and normalized by the downwelling solar irradiance at each sensor wavelength, λ, in the visible domain with units of sr^{-1}. The coefficients were derived using version 2 of the NASA bio-Optical Marine Algorithm Data set (NOMAD). The functional form of the OC3 algorithm is as follows:

$$Chla = 10^{(0.2412 - 2.0546\,\mathrm{R} + 1.1776\,\mathrm{R}^2 - 0.5538\,\mathrm{R}^3 - 0.4570\mathrm{R}^4)} \quad (2)$$

$$R = log_{10}\,(Rrs_{561}^{443} > Rrs_{561}^{482}) \quad (3)$$

where *Chla* represents the chlorophyll-a concentration (mg m^{-3}), Rrs is the remote sensing reflectance (sr^{-1}) and R is the blue-to-green band ratio (unitless). Rrs 443, Rrs 482, Rrs 561, and the coefficient for OLI sensor, a_0 to a_4. However, these operational OC3L algorithms are only applicable in the clear water [16].

For retrieving Chl-a from Sentinel-2 MSI, the C2RCC is used for Case-2 waters. *Rrs* 443, *Rrs* 490 and *Rrs* 510 from blue band and Rrs 560 from green band were applied in this case. A non-linear relationship of two sets variables were established and tuneable coefficients of C2RCC model were optimised. In this study, the spectral distribution of ocean colour data corresponds to the input variables set, hence produce output set consists of Chl-a concentration, total suspended material concentration and the concentration of DOM. Hence, in this paper, the performance of C2RCC compared with results of in situ measurement for Chl-a retrieval.

RMSE and R^2 coefficient are applied to validate the Chl-a retrieved at three sampling stations. The RMSE equation will be computed using equation below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Chla_s - Chla_g)^2}{n}} \quad (4)$$

where $Chla_s$ represents the estimated Chl-a concentration (mg m^{-3}) from satellite and $Chla_g$ is Chl-a concentration from in situ measurement (mg m^{-3}).

III. RESULTS AND DISCUSSION

The study produced the remote sensing reflectance (*Rrs*) and Chl-a from OC3 and C2RCC. Chl-a retrieved from satellite were matched up with in situ Chl-a based on the nearest date and location of measurement. The availability of match-up data in Johor water is limited due to cloud cover, hence weaken the sensibility of the algorithm towards the Case-2 water. Chl-a retrieved from OC3L and C2RCC were plotted with in situ Chl-a, as shown in Fig. 2.

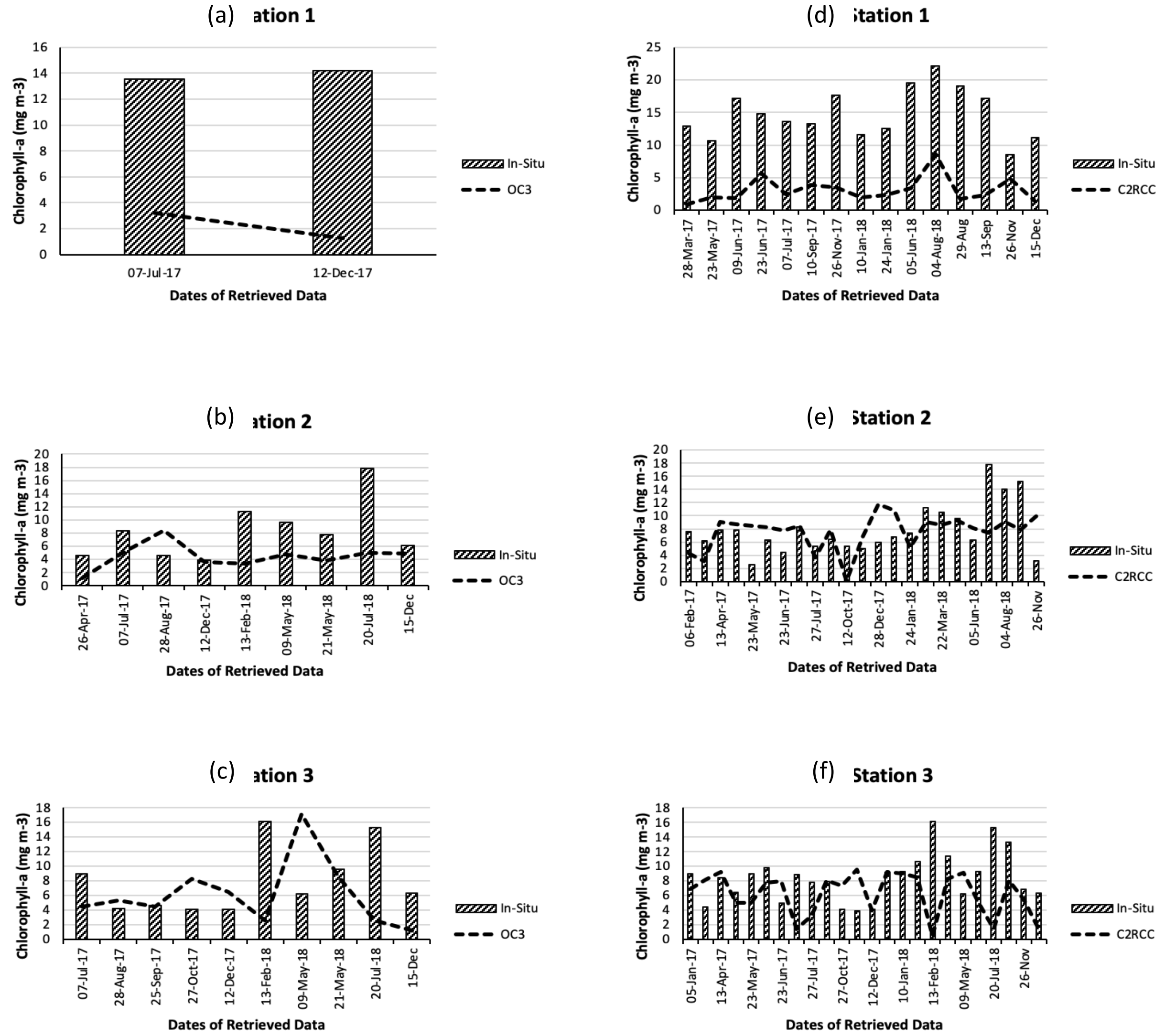

Fig. 2. Temporal variations of in-situ Chl-a, OC3L-retrieved Chl-a (a, b and c) and C2RCC-retrieved Chl-a (d, e and f) in three sampling stations.

Obviously, the result shows underestimation and overestimation Chl-a retrieved from the OC3L and neural network of Johor waters. The Chl-a retrieved was underestimated at S1, meanwhile Chl-a was overestimated in S2 and S3. Due to the natural and human activities along Johor Straits, Chl-a absorption ratio can exceed the observed. Rapid urbanization of the area affects to lower blue-to-green absorption and higher blue-to-green reflectance resulted in underestimation of Chl-a over S1. Existence of living plants and animals (i.e. seagrass bed and phytoplankton), nutrient enrichment and runoff of sediments from numerous rivers along Straits of Johor also affect the Chl-a estimation. Since the blue light strongly absorbed by CDOM and phytoplankton, increases CDOM also increases the blue-to-green absorption, hence decreases in blue-to-green reflectance ratio that can be misinterpreted as the higher chlorophyll concentration [16], at S2 and S3, on 28th August 2017, 27th October 2017, 12th December 2017 and 9th May 2018. Meanwhile, on 12th October 2017 and 13th February 2018, the increase of blue-to-green ratio causing the low Chl-a retrieval.

The Chl-a retrieved by OC3L and C2RCC, was plotted against the in-situ Chl-a collected from three sampling stations, and the regression line were calculated to evaluate algorithm performance as shown in Fig. 3. Table 1 presented the RMSE and R^2 value for Johor water.

Table 1. RMSE and R2 value calculated from OC3 and C2RCC.

Bio-optical algorithms	**OC3**	**C2RCC**
RMSE (m)	7.264	7.334
R^2	0.44	0.55

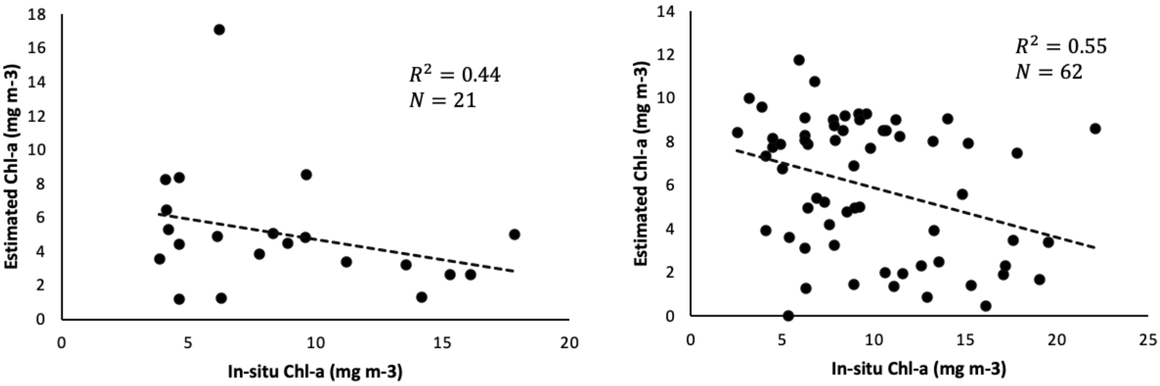

Fig. 3. Statistical regression of in-situ Chl-a, OC3L-retrieved Chl-a and C2RCC-retrieved Chl-a in Johor water.

The RMSE values of OC3 and C2RCC were 7.264 m and 7.334 m, meanwhile R2 values were 0.44 and 0.55. Based on the statistical analysis done for both algorithms, the performance of OC3L from OLI is trivial and not very suitable to Case-2 water, compared to performance of C2RCC for MSI. The OC3L more accurately and efficiently estimated in clear or more oceanic water that dominated by phytoplankton where the optical properties and bottom reflectance is negligible [5, 10]. The statistical analysis of C2RCC has shown a slightly better results compared to OC3L. C2RCC is a multi-mission ocean colour processor, relies on a large database of simulated water leaving reflectance, and related top-of- atmosphere radiances, and inverted by neural networks. The processor has been validated for the different sensors, with good results for Case 2 waters. Despite the relatively good overall accuracy of the C2RCC products, several issues still remain to be addressed and further analysis should include studies on the spatial, vertical, and temporal variability of the water quality based on the Chl-a products. Future work should also extend this method by offering the water quality products and ecological state estimation.

IV. CONCLUSION

With the help of multispectral satellite, this study assesses the performance of OC3L and C2RCC processor in retrieving Chl-a in West Johor Straits using Landsat MSI and Sentinel MSI imagery. The results show the underestimation and overestimation Chl-a. Chl-a concentration estimated from both algorithms were evaluated and concurrently correlated with in situ data at sampling stations ($R^2 = 0.44$ from OC3L and $R^2 = 0.55$ from C2RCC). The seasonal spatial and temporal of Chl-a has not been able to be clarified due to the small number of MSI and OLI images available for this study. Therefore, locally tuned algorithm and new techniques, such as machine learning techniques is necessary for Chl-a retrieval to improve Chl-a estimation in Straits of Johor and to produce a better inversion result. Despite differences in their spatial, spectral, and temporal characteristics, this paper shows that both processor, OC3L and C2RCC appears to be feasible and can play significant roles in Chl-a mapping and monitoring water quality.

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