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The Performance of Chlorophyll-a Distribution Estimation by Using Ratio Algorithm on Landsat-8 in Sungai Merbok Estuary.

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Abstract

The presence of phytoplankton in the water is important as the primary food source of various aquatic lives as well as to determine its pollution level. Among many, the ratio algorithm is one of the approaches in remote sensing used to detect chlorophyll-a in the phytoplankton for its distribution and monitoring. However, some algorithms usages are limited to spatial, temporal, and other factors, hence the performance evaluation of algorithms developed are indeed important for robust observation and monitoring purposes. This study explores the applicability of ratio algorithms for estimation of the chl-a concentration at Sungai Merbok by assessing chl-a distribution pattern built by the algorithms and evaluating each algorithm for their errors compared to in-situ data. The distribution models generated from the algorithms were utilizing Landsat-8 satellite images with B-G and B-R bands ratio. The statistical analysis employed regression models such as p-value, r, R2, and RMSE for both algorithms' performance evaluations. Overall, the chl-a distribution along Sungai Merbok shows a safe concentration with fluctuation in a wide interval, however, both algorithms predicted much low concentration values with narrow and consistent variations. On average, Sungai Merbok recorded 9.52 mg/L chl-a concentration, while B-G and B-R algorithm predicted a lower average at 1.04 and 2.83 mg/L respectively. Although B-G and B-R algorithms both have a significant relation with strong correlation, B-G shows a higher coefficient of determination with 65% variation compared to B-R with about 60%. B-R ratio performed better with a lower RMSE value of 10.22 as compared to 11.48 for B-G. The findings of this study perhaps will be helpful to the traditional fishermen, local entrepreneurs, and relevant authorities for sustainable fisheries resources and management.

Keywords: Chlorophyll-a, Ratio Algorithm, Landsat-8, Chlorophyll Distribution, Sungai Merbok

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Introduction

One of the most important parameters of water quality studied by researchers is the concentration of chlorophyll-a (chl-a) produced by phytoplankton in the sea. Both phytoplankton and chl-a concentration are closely related given that the latter are considered as indicator for the abundance of the former (Pham et al., 2019). The concentration of chl-a determines the number of phytoplankton available in the sea whether it is lower or higher than the optimum level. In-situ sampling is frequently used given that it often provides accurate data, but this process requires longer time, and it cannot guarantee a simultaneous dataset of water quality at regional or greater scale (Markogianni et. al., 2020). Apart of in-situ sampling which is conducted by collecting water samples from the selected waterbody, remote sensing technique is also useful to determine the concentration of chl-a. Remote sensing involves the monitoring of sea appearances with satellite where it produces images consist of several spectral bands (Buditama et al., 2017). Through remote sensing, researchers have come out with different algorithms to determine the concentration of chl-a in different waterbodies. Different waterbodies adaptation could possibly provide different algorithms to suit them.

These algorithms are extremely important for estimating chl-a concentration in wide waterbody region where in-situ data coverage is limited. Several attempts have been made to determine whether these algorithms are applicable at local waterbodies by comparing its accuracy with the measurement of field data (in-situ) collected. The recent study that successfully employed remote sensing technique with positive results was the attempt to determine the suitability of using bio-optical ocean color (OC) algorithm from Landsat-8 OLI/TIRS and Sentinel-2 MSI for estimation of chl-a concentration in Northern Coastal Bay of Bengal (Poddar et. al., 2019). Earlier, Kabbara et. al. (2008) in Tripoli have developed 2 ratio algorithms for retrieval of chl-a concentration which tested on Landsat-7 ETM+ and found that the algorithms performed well. After 10 years, Boucher et. al. (2018) had again tested the algorithms developed, and had discrepancy of 2- and 5-days interval at few lakes located in Maine and New Hampshire, USA, which they found that the algorithms were better to estimate the chl-a concentration of below 4 mg/L.

The complexity of in-situ data for continuous environment monitoring consumed a lot of money and time. Remote sensing applications are helpful to the stakeholders, especially in assessing remote area with low accessibility and estimation for thorough field processing method to acquire data such as chl-a (Ghozalideh et. al., 2016). The distribution of chl-a is important to be monitored and very useful to several agencies in Malaysia such as Malaysia Space Agency (MYSA) and Fishery Department for estimating areas with fish resources. We have known that ratio algorithms performed appropriately well and has been tested in middle east (Kabbara et al., 2008) and USA (Boucher et al., 2018) waterbodies located in the subtropical zone (tropic of cancer). However, the performance of the developed algorithms has not yet tested in equatorial water and estuary, especially in Malaysia. Thus, this study aims to ascertain the performance of ratio algorithms utilizing red, green, and blue bands from Landsat-8 satellite images for it best fitted between the two different bands ratio to estimates the chl-a concentration at Sungai Merbok estuary, Kedah.

Sungai Merbok is famous for its mangrove estuary which constantly receives the flow of seawater originated from Malacca Straits and freshwater from streams and land runoffs (Figure 1). Merbok estuary has over 8000 hectares at which 5000 hectares of it are consists of Mangrove Forest Reserved (MFR) and 1500 hectares of reclaimed mangrove, while the rest of it are water ways (Maznah et. al., 2016). Estuary areas are different from sandy beach and rocky shore coastal area, with the presence of mangrove trees at the area and along the river it has provide sources of nutrients for the growth of phytoplankton that indicates higher chl-a concentration. Phytoplankton obtained nutrients such as nitrogen, phosphorus, and potassium from mangrove ecosystems in the form of dissolve organic matter (DOM). These DOM are produced from the decomposition of falling leaves, branches and other litter fall in the mangrove ecosystem (Saifullah et. al., 2015).

Two objectives that have been carried out with some restraint during the study to suffice the evaluation of the algorithms' performance for estimation of chl-a distribution, and they were to identify the distribution of chl-a along the river by in situ and remotely sensed data from the developed algorithms of B-G and B-R ratio, and to evaluate the performance of each algorithm for their differences and errors. It is important to utilize remote sensing techniques especially in aquatic ecosystem, where phytoplankton act as primary producer which is also a staple food by zooplankton and later the fish, as main consumer within the area (Napiórkowska-Krzebietke, 2017). This study hoping to assist our traditional fishermen to ease their search for a region with high catch possibilities instead of spending more effort on exploring the water territory. Advantages also expand to the aquaculture industries and local entrepreneurs for appropriate site selections, early mitigation and action against algae blooming phenomena, as fish cage, floating restaurant and hotel, and shipping activities are the prospects economy along the river.

Methods

The area of interest for this study was focused along the Sungai Merbok, Kedah. Due to the movement restriction in 2020 and 2021 restricted for a new set of data collection planned, however a set of chl-a data collected in year 2015 were used instead of recent data. The data was collected for about 23 km along the Sungai Merbok surface water and consist of 20 sample stations (Figure 1). In line with that, Landsat-8 OLI/TIRS satellite images close to the date were used in this study considered the best choice based on its availability. This is due to the fact that Landsat-8 require 16 days to complete the imaging process of entire Earth and to revisit about the same location (Silvestri et. al., 2021), and within that same year satellite images from Sentinel-2 was not yet available. The satellite images used in this study dated 20th October 2015 from Path 128; Row 056 which a Level 2 collection of science (L2SP) images, and there was a gap of 8 days which possibly could contribute to the uncertainty between in-situ data and remotely sensed data generated from the algorithms. To identify the distribution pattern of chl-a, there were two separated processes for in-situ data and satellite images. The in-situ data were interpolated using Inverse Distance Weight (IDW) method (Eq. 1) executed on ArcGIS 10.6 to represents the measured chl-a distributions along the river (Figure 2).

$$V_i = \frac{\sum_{j=1}^{n} \frac{1}{{d_{ij}}^{p}} V_j}{\sum_{j=1}^{n} \frac{1}{{d_{ii}}^{p}}} \qquad (1)$$

Where, V_i represents the value of known point, n represents the number of sample stations, d_{ij} represents the distance to the known point, and p is the user selected exponential.

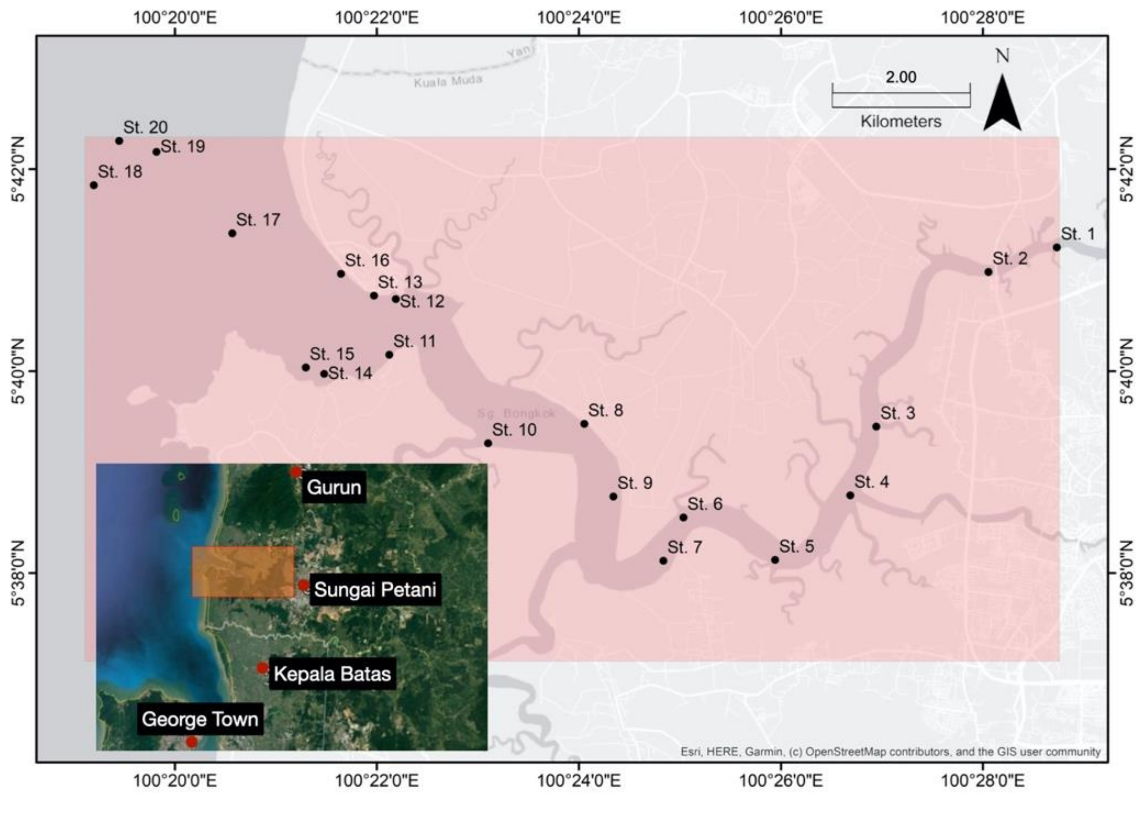


Figure 1. The location of selected study area near Northern Malaysia marked with 20 sampling stations for chlorophyll-a concentration data along the Sungai Merbok area from inland Jetty outward to the estuary and ended at sea area.

On the other hand, the satellite images were processed using surface builder by applying the ratio algorithms to represents the remotely sensed chl-a distributions (Figure 3). The two algorithms were originally formulated by matching satellite images reflectance of Landsat-7 ETM+ and in-situ data developed by Kabbara et. al. (2008), using blue and green bands ratio which in this study they are refers to as Blue-Green (B-G) ratio algorithm (Eq. 2), where the blue band is $B2$ and green band is $B3$, and the other algorithm using blue and red bands ratio that this study refers to as Blue-Red (B-R) ratio algorithm (Eq. 3), where the red band is $B4$. However, before the process begun, the satellite images were converted into surface reflectance (unitless digital number) which suitable for algorithm calculation, by using pi (π = 3.1416) division method (Poddar et al., 2019). The value of data at each station was then extracted and further analyzed.

$$ln(Chlorophyll\ a) = 1.67 - 3.94\ ln(B2) + 3.78\ ln(B3) \tag{2}$$

$$\ln(Chlorphyll\ a) = 6.92274 - 5.75815\ [\ln(B2)/\ln(B4)] \tag{3}$$

To assess the performance of algorithms selected, the regression model was used from data extracted, and statistical analysis was carried out to find the significant relationship between data estimated values (P), the correlation coefficient (r), coefficient determination (R^2) and the root mean square error ($RMSE$). The P value was used to determine whether the pattern show by the chl-a distribution from algorithms is statistically significant related or not, after the r value is acquired. The $RMSE$ (Eq. 4) was used to informed on precision of the predicted value over the measured value. An algorithm with lowest $RMSE$ value is considered to be the most precise given that it indicates a small error to the in-situ data (Ohara et al., 2018). The r value (Eq. 5) was analyzed to see the correlation of both measured and predicted value, to observed either the relationship between them is weak or strong. While R^2 (Eq. 6), in the linear regression was used to show the proportion of variance between the measured and the value extracted from algorithms. The higher the R^2 value the better fit the algorithm performance.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{insitu} - x_{algorithm})^2}{n}} \tag{4}$$

$$r = \frac{n\sum[(X_{insitu} - X_{algorithm})] - [(\sum X_{algorithm})(\sum X_{insitu})]}{\sqrt{[n(\sum X_{insitu}{}^2) - (\sum X_{insitu})^2]}.\sqrt{[n(\sum X_{algorithm}{}^2) - (\sum X_{algorithm})^2]}} \tag{5}$$

$$Coefficient\ Determination\ (R^2) = (Correlation\ Coefficient)^2 \tag{6}$$

Where, X_{insitu} represents concentration of chl-a from the in-situ collected data, $X_{algorithm}$ represents concentration of chl-a from the algorithms, and n represents number of sample stations.

Result and Discussion

The in-situ measured of chl-a concentration (Table 1/Figure 2) shows a wide interval of data that ranged from 2.22 to 27.56 mg/L. While, in average, Sungai Merbok recorded 9.52 mg/L of chl-a concentration and considered as safe and common for estuary that does not contribute to harmful algal blooms (Ayeni & Odume, 2020). Based on the previous studies on mangrove areas, it was expected that stations which are near to the Mangrove Forest Reserved (MFR) would show a higher chl-a concentration, however the two stations located near to the MFR; St. 1 (Jeti Semeling) and St. 2 (Pulau Tiga), did not record the highest concentration but among the lowest which are 2.7960 mg/L and 2.2234 mg/L respectively. The highest chl-a concentration was found further away from the MFR instead, which the two highest were at St. 16 (Pantai Tg. Dawai) followed by St. 14 (Teluk Nipah) with concentration of 27.5635 mg/L and 23.6264 mg/L respectively. Along with affected from water movement and tides, this finding was found to be supported by anoxic and hypoxic event that could commonly happen in estuary region where it is susceptible due to the density stratification when freshwater flows seaward over denser and more saline marine water (Mohd-Din et. al., 2020).

The pattern of chl-a distribution developed from the interpolated in-situ data by IDW method (Figure 2) shows that MFR is not only the main contributor of nutrient at those stations, but phytoplankton also does obtained nutrients from waste products of various human activities. Along the river we observed many catchments outlet going into it and among the stations, they were also points of which these outlets are located. Active agriculture activities are also the main supply of nutrients (nitrates, nitrite, ammonium and other) to the river and estuary (Bužančić et. al., 2016) not just that, the rigorous urbanization process produces runoff (detergent, waste discharge and others) also contribute to the fluctuation of chl-a concentration (Ruslan et. al., 2014) and worse to the excessive of nutrient which can lead to eutrophication event. Eutrophication is lethal to aquatic organism, where dissolved oxygen (DO) in the water is being absorbed massively by phytoplankton for respiration process and consequential of suffocating other organisms that occupy the same area (Maznah et al., 2016).

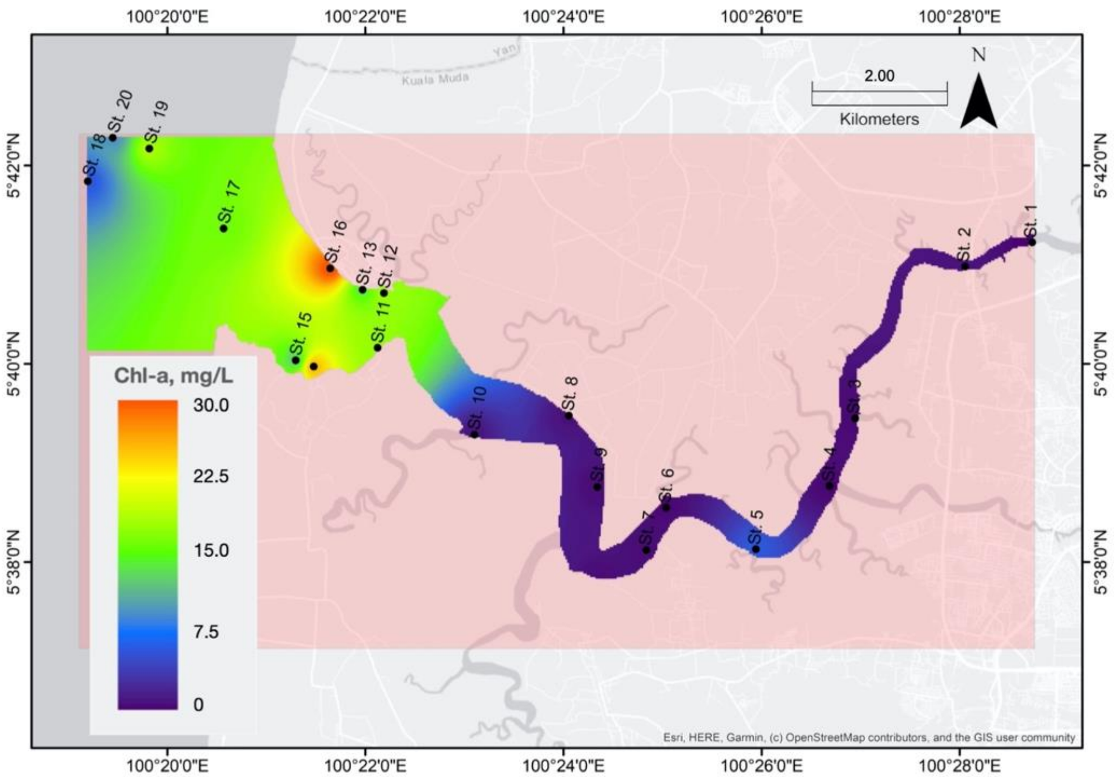
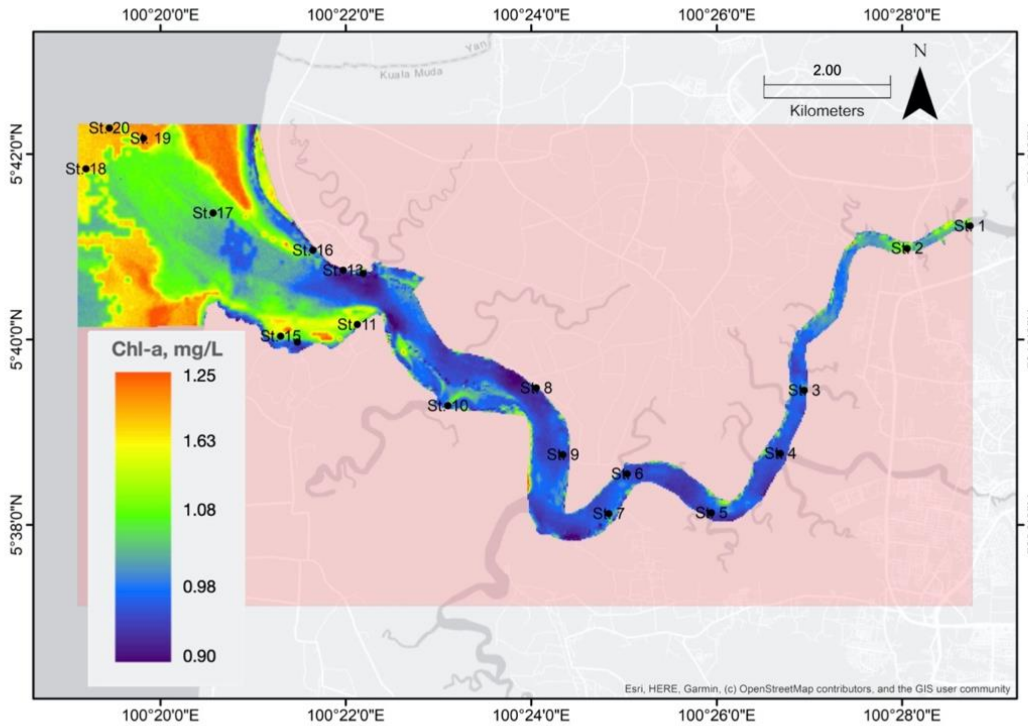


Figure 2. The interpolated model of chlorophyll-a concentration from in-situ data to represent Sungai Merbok chlorophyll-a distribution

In contrast, the pattern of distribution from the algorithm shows only slight differences from B-G and B-R ratio compared to the in-situ data. The obvious difference in pattern was at the early St.1 and St.2 areas where both algorithms show a higher value, and this may be due to the jetty and other manmade structures within that area. Landsat-8 pixel for red, green, and blue bands has a square shape with 30 m x 30 m area, thus it should dissolve the value of any color features within 900 m^2 area and might affecting the chl-a prediction especially at the narrower area of the river. The algorithms were applied to every pixel of satellite image available in the study area, thus giving a full-scale view representing the chl-a distribution within the river (Figure 3) as compared to the distribution for in-situ measured chl-a (Figure 2). The in-situ data was an interpolated surface, this factor is one of the reasons to the variations of pattern as we compared them altogether. Another spot that shows slightly different in pattern was at the river mouth, the estuary. The in-situ as compared to the B-R ratio showing an inverted pattern where in-situ value was higher at estuary and getting lower seaward, but the B-R ratio shows the vice-versa. However, the B-G ratio pattern shows an increased pattern from the river to seaward which follow the water salinity gradient (Mohd-Din et. al., 2020). Cloud cover hovering over the study area could also affecting the prediction, although lower percentage (<10%) of cloud were observed in the study area from the satellite images (Boucher et. al., 2018).

(a)



(b)

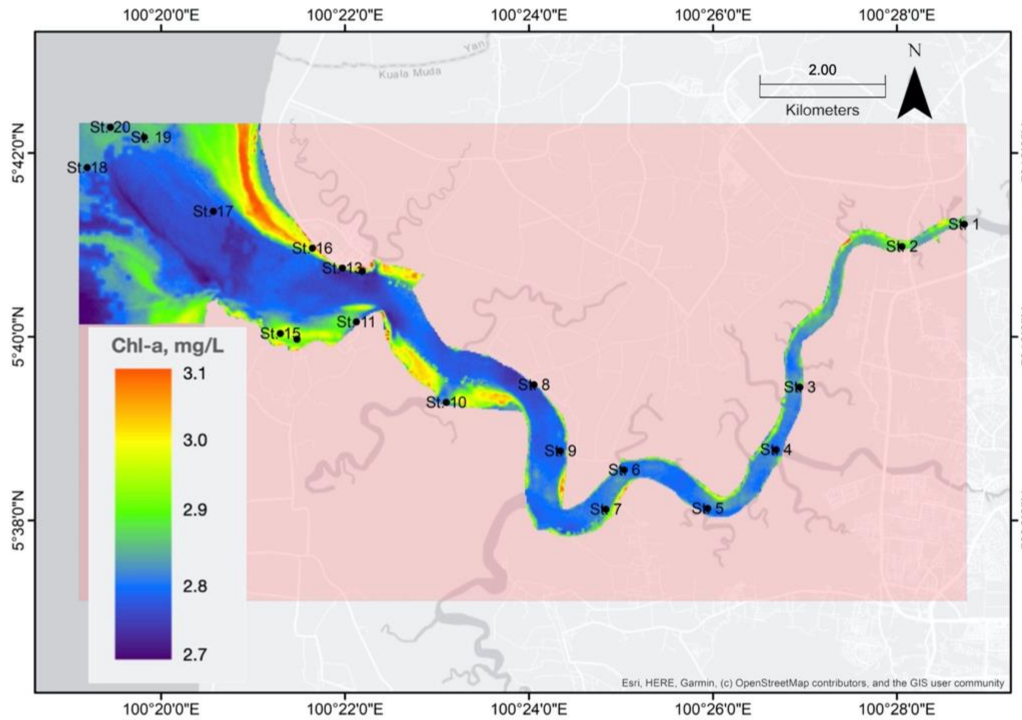


Figure 3. The distributions of chlorophyll-a concentration generated from the (a) B-G and (b) B-R ratio algorithms using Landsat-8 satellite images interpolated model of chlorophyll-a concentration from in-situ data to represent Sungai Merbok chlorophyll-a distribution

All the distribution patterns between those models from in-situ and algorithms showing lower chl-a value at the middle area along the river and higher towards the riverbanks. As during data acquisition process, we observed many human activities near or even inside the river area which consist of boating, restaurant, hotel, aquaculture and other. Many researchers had found that, human intervention to the waterbody either directly or indirectly will result to impacting the pattern distribution of chl-a (Pham et al., 2019; Markogianni et. al., 2020). The presence of phytoplankton is important given that it is the natural source of food for fishes in the area, however when their concentration is exceeding, not every organism will be benefited. The concentration of phytoplankton by the detection chl-a is a good way to monitor the level of pollution in the river itself. This is supported by Seyma and Ersin (2018) which states that the increase of chl-a concentration is a signal of organic contamination in the marine environment and the elevated levels of nutrients in the marine environment are pollution indicators resulted from human activities, this seems align to the Sungai Merbok condition.

In terms of the algorithm's performance, both algorithms were significantly correlated to the in-situ data despite having a slight difference in the pattern of distribution. B-G ratio algorithm has lower *RMSE* value as compared to B-R ratio with different of 1.26 mg/L between the two and they were 11.48 mg/L and 10.22 mg/L respectively. The bigger value of concentrations yield from B-R ratio is the reason for the lower *RMSE* value where it reduces the differences of remotely sensed to the measured data. However, when referring to the data, the values produced for *RMSE* are consider huge which indicates that the estimated concentration of chl-a is not closely accurate to the in-situ data. There are various reasons that led to the underestimation of these algorithm to the in-situ data and thus affecting accuracy and performance of the algorithms.

Table 1. The chlorophyll-a concentration according to 20 stations of data acquired from in-situ and extracted from the processed satellite images using Ratio Algorithms

Station	In-situ (mg/L)	B-G Ratio (mg/L)	B-R Ratio (mg/L)
1	2.2234	0.9682	2.7448
2	2.7960	0.9742	2.7439
3	2.3567	0.9709	2.7277
4	2.2953	0.9730	2.7361
5	7.1756	0.9955	2.7712
6	2.2905	1.0011	2.7978
7	2.4752	1.0008	2.7943
8	2.6193	1.0246	2.8366
9	2.4942	1.0310	2.8363
10	2.7994	1.0160	2.8041
11	16.6207	1.0089	2.7984
12	16.7586	1.0711	2.8754
13	13.9698	1.0847	2.8879
14	23.6264	1.0552	2.8527
15	12.6267	1.0600	2.8531
16	27.5635	1.1949	3.0253
17	15.4036	1.0903	2.8852
18	6.9129	1.0605	2.8560
19	17.3663	1.0876	2.8718
20	10.0286	1.0732	2.8688

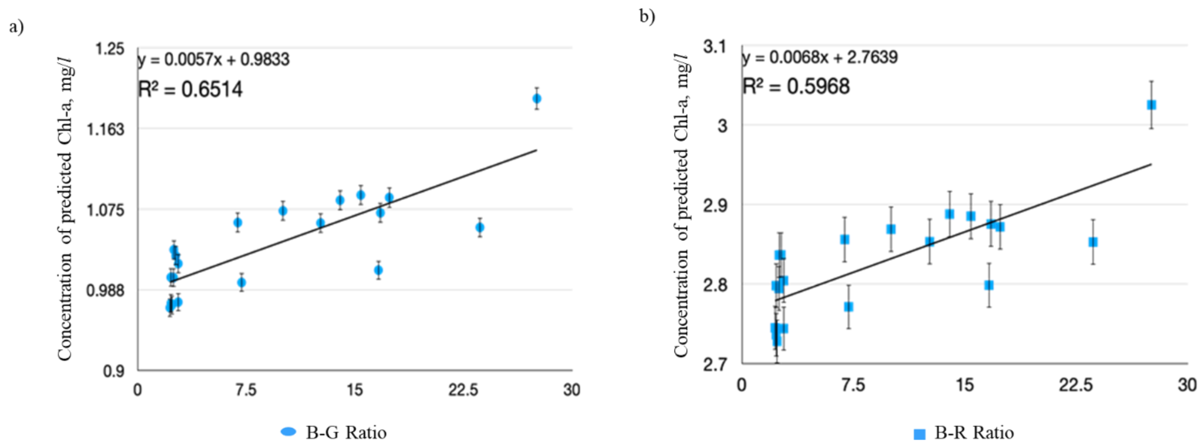


Figure 4. The chlorophyll-a concentration relation along the 20 stations of in-situ values against remotely sensed values extracted from the processed satellite images using (a) B-G and (b) B-R ratio Algorithms

The underestimation of chl-a concentration for B-G ratio stemming from the location of these stations which are located inland and coastal water areas. Both inland and coastal water are optically complex at which ratios of reflectance band are not sensitive enough to the change of chl-a concentrations due to more lights are being absorbed by colored dissolved organic materials (CDOM) (Keith et. al., 2018). Another factor that contributes to the underestimation of chl-a concentration is due to the pigment package effect of phytoplankton which causing the absorption by chl-a does not increase even though there is a huge concentration of chl-a detected in those stations (Watanabe et al., 2017). The pigment package effect is influenced by the size of phytoplankton and its respective content of pigment (Le et. al., 2008).

Table 2. The algorithms performance for estimation of chlorophyll-a concentration based on regression model that consist of P, r, R^2 and $RMSE$ value analyzed from extracted values of Landsat-8 satellite images using B-G and B-R ratio algorithms

Algorithm	P	r	R^2	$RMSE$
B-G Ratio	0.000017, $P < 0.05$	+0.807	0.651	11.4829
B-R Ratio	0.000065, $P < 0.05$	+0.773	0.597	10.2246

Besides, blue band (used in both algorithms) was reported undergone scattering due to the turbid condition in the water (Mansaray et al., 2021) which affecting the ability of both algorithms to underestimate the chl-a concentration. This study observed and acknowledged the turbid condition of the water in Sungai Merbok area due to the presence dissolved organic materials (DOM). The presence of DOM will cause the blue band to have a low reflectance in the water but strong absorption instead, thus affecting its ability to estimate the concentration of chl-a. Apart from blue band, the properties of green band (Band 3 used in B-G ratio processing) also reported suffers from strong scattering caused by suspended sediments in the water and causing its ability to reflected from chl-a is weaker (Ye et. al., 2016) and non-algal particle such as sediment possesses a high absorbance which it could directly affects the performance of B-G ratio algorithms in estimating chl-a concentration (Salem et. al., 2017).

It is worth to acknowledged that the satellite image used in this study was dated on 12th October 2015 which a slight of 8 days gap. These data inconsistencies might cause by several factors such as spatial heterogeneity in distribution of phytoplankton within the river such as weather changes due to rain or wind which could change of the density of phytoplankton between the collected in-situ sample and time taken to obtain satellite images (Boucher et al., 2018). Both algorithms have positive value of correlation coefficient (r); where the r value of B-G and B-R ratio algorithm is +0.807 and +0.773 respectively. B-G ratio algorithm has higher r value than B-R ratio algorithm, indicating that it has stronger relationship with in-situ data. The coefficient of determination (R^2) for B-G and B-R ratio algorithm is 0.651 and 0.597 respectively, indicating that the former had about 65% fitness to the in-situ data while the latter had about 60% fitness to the in-situ data to represent chl-a concentration at Sungai Merbok. As this study only focusing on single scene study area, these findings were aligned but slightly lower compared to the result discover by previous studies which about 72% fitness for both algorithms at Tripoli and about 67% for B-G ratio and 69% fitness for B-G ratio at Maine USA (Boucher et al., 2018; Kabbara et. al., 2008).

Conclusion

The distribution of chl-a along the Sungai Merbok shows a safe and common concentration of chl-a even in a wide interval with fluctuation of data that ranged from 2.22 to 27.56 mg/L with difference of 25.34 mg/L and average of 9.52 mg/L, and the distribution for B-G and B-R ratio algorithm were found to be more stable and consistent but underestimated. The B-G ratio ranged from 0.96 to 1.20 mg/L with difference of 0.2267 mg/L and average of 1.04 mg/L, while the B-R ratio ranged from 2.72 to 3.03 mg/L with difference of 0.2976 mg/L average of 2.83 mg/L. The pattern of distribution for both algorithms are slightly different when compared to the measured in-situ pattern of distribution due to underestimation of predicted values. The performance of both algorithms found to be satisfying, where the distribution relationships are significant with $P < 0.05$, the correlation coefficient of them were positive and considered strong as B-G ratio was +0.807 and B-R ratio was +0.773. Due to that, B-G ratio shown a higher coefficient determination with about 65% fitted compared to B-R ratio with about 60% fitted. As both algorithms underestimating the chl-a concentration of the study area, however, B-R ratio algorithm produced lower *RMSE* value with 10.22 compared to B-G ratio which 11.48. Therefore, it can be concluded that chl-a concentration obtained from B-R ratio algorithm has a better performance and significant with in-situ as compared to B-G ratio algorithm for Sungai Merbok, Northern Malaysia. The findings of this study hopefully could assist our traditional fishermen for their small-scale fishing activities to focus their effort at high probability catch area, while local authorities to govern proper environment for a sustainable fisheries resource and expand to the industry players for appropriate sites and activities along the river to avoid adverse effects in the future.

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