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CHLOROPHYLL-A ESTIMATION AND RELATIONSHIP ANALYSIS WITH SEA SURFACE TEMPERATURE AND FISH DIVERSITY

NOR AIZAM ADNAN[1]*, RAIHAN MAISARA AHMAD IZDIHAR[1], FARAH QISTINA SHAHIBUL FADILAH[1], SITI TAFZILMERIAM SHEIKH ABDUL KADIR[2,4,5], AISYAH MAT SULAIMAN[3], SITI ASMAL MAT PIAH[3], YING GIAT SEAH[3,5] AND AIDY M MUSLIM[2]

[1]Centre of Studies Surveying Science and Geomatics, Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor, Malaysia. [2]Ecological Resilient Research Program, Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu (UMT), 21030 Kuala Nerus, Terengganu, Malaysia. [3]Faculty of Fisheries and Food Science, Universiti Malaysia Terengganu (UMT), 21030 Kuala Nerus, Terengganu, Malaysia. [4]Mangrove Research Unit (MARU), Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia. [5]South China Sea Repository and Reference Centre, Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu (UMT), 21030 Kuala Nerus, Terengganu, Malaysia.

**Corresponding author: nor_aizam@uitm.edu.my*
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Abstract: Phytoplanktons are sensitive to temperature changes and can only thrive in certain sea surface temperatures (SST). To determine the relationship between the two variables, the Chlorophyll (Chl-a) in phytoplanktons around the Bidong Island, Terengganu was estimated using the Sentinel-2 Multispectral Instrument (MSI) running two algorithms - C2RCC and OC3M - between 2015 and 2016. The OC3M algorithm resulted in better Chl-a estimation values with RMSE of 0.05 and MAE of 0.049. The relationship analysis was done using linear regression between OC3M Chl-a and MODIS SST. The regression analysis found that the Chl-a variation in the area was only weakly affected by the SST, with highest negative correlation of -0.2867 in September 2016. Fish sampling in the study area showed that there was significant difference in the diversity of fish species between the years 2015 and 2016. Comparison with Chl-a distribution showed that high species diversity and abundance of fish reduces the amount of Chl-a = in the water. Thus, this research can be further explored for sustainable fish production in the future.

Keywords: Sentinel, remote sensing, chlorophyll, sea surface temperature, fish species diversity.

Introduction

Phytoplanktons are plant-like organisms that use chlorophyll, sunlight and other light-harvesting pigments to carry out photosynthesis, which produces carbohydrates and releases oxygen in the water column (Minnett, 2014; Long, 2019; Cantrell & Lam, 2021). Chlorophylls are pigments in the chloroplast of phytoplankton. It is a pigment that reflects certain wavelengths, most commonly in the green band, hence, its green appearance (Lichtenstein & Walsh, 2019). Chlorophyll in water may alter the way it receives and reflects sunlight, this enables scientists to monitor the phytoplankton composition and distribution (Minnett, 2014). Chlorophyll pigments have such a unique and distinguishable spectral signature as they retain blue (and red) light and strongly reflect green, thereby influencing ocean hue.

Both the physical and biological features of Chlorophyll (Chl-a) can be observed by satellite remote sensing. Therefore, multispectral observations from aerial or space-borne sensors enable the derivation of phytoplankton concentration (Butler *et al*., 2019). To date, no single algorithm can provide accurate quantitative information across all water types. Empirical formulas that use reflectance relationships in the blue and green spectral regions are often used to extract Chl-a in open ocean waters, where water components appear to covariate with phytoplankton.

Phytoplankton clustering relies on sunlight, temperature and nutrient levels that are available (Park *et al*., 2011; Kouketsu *et al*., 2016). Cold environment suppresses the production of phytoplankton and affects its growth and concentration. Contrary to the effects of cold, higher temperature of the ocean with the help of other factors can promote the growth of phytoplankton, hence, increasing the concentration of chlorophyll. However, this rise in temperature can cause algal bloom, where overlay chlorophyll concentrated water poisons fish and reduces the oxygen levels in the sea (Hu, Lee & Franz, 2012). This phenomenon will also affect other sea creatures and plants. As a primary food source, chlorophyll concentration has a significant effect on fish diversity and compositions (Levinton, 2019).

The variability in sea surface temperature (SST) have been shown to have great effect on the concentration of phytoplankton. SST is influenced by the sun reflection (atmosphere) which is a vital element in the ocean environment. The variations in SST can also cause changes in the climate, ocean content and the overall ocean climate status (Hussein *et al*., 2021). SST measurements are an important indicator of global climate changes and nature of the ocean. Ocean temperature is used mainly used for monitoring, which include weather forecasting, tracking climate changes and ocean fish production management.

According to a study by Nurdin *et al*. (2015) on an area of archipelagic waters off Spermonde in Indonesia, there is a significant relationship between fish catch with SST and Chl-a. The study obtained a correlation coefficient R of 0.7, showing that catch will increase with the rise in SST and Chl-a concentration. The coefficient of determination (r^2) of 0.5 demonstrates that SST and Chl-a contributed 49.6% to the variation in changes of the catch of fish (*R. kanagurta*), while the remaining of 50.4% was influenced by other factors. Thus, this study aimed to compare different Chl-a extraction algorithms, determine the relationship between Chl-a and SST and its effects on the fish species diversity, composition and species richness of Bidong Island, Terengganu.

Study Area

Located on the east coast of Peninsular Malaysia, Terengganu is a state facing the South China Sea with long wide beaches that stretches from Kuala Besut at latitude and longitude (5° 50’ 45”, 102° 32’ 08”) up to Kuala Kemaman, Chukai (4° 14’ 17”, 103° 26’ 33”). The state is mostly hot and humid all year round with temperature averaging from 28°C to 30°C during the day. Terengganu is constantly exposed to moderate rainfall and breeze all year round. The state’s coastal water temperature is warmest from April until July and colder waters are expected during the monsoon season (Average Weather in Kuala Terengganu Malaysia, 2019). During the monsoon, the state discourages fishing due to the harsh offshore weather.

Bidong Island is a small island off the coast of Terengganu and is 10 nautical miles from Pulau Redang (Malaysia Liveaboards, 2020). The tiny 1 km² island is surrounded by beautiful corals and marine life. The surrounding area of the island is a haven for fish and fishing is a regulated activity (Figure 1). Known for its sea products, the majority of the Terengganu state income comes from fisheries and tourism. Due to this factor, fishing areas and fish production are closely regulated and monitored to maintain the economy and understand the coastal ecosystem better (Rahim & Saat, 2018).

Data and Methods

This study has five stages: Data acquisition, data pre-processing, image processing, verification analysis and regression analysis as shown in Figure 2. Two types of sensors data were used. One is the Sentinel 2 Level-1C of 10 m resolution with 13 spectral channels in the visible, VNIR and SWIR were obtained from https://scihub.copernicus.eu/. Two is the Moderate Resolution Imaging Spectroradiometer Satellite (MODIS-Aqua) Level-3 with 4 km resolution. Sentinel 2 Level-1C MSI images for Chl-a extraction were downloaded from Sentinel Open Access Hub (Copernicus) website for 10th August 2015, 20th August 2015, 3rd September 2016 and 23rd

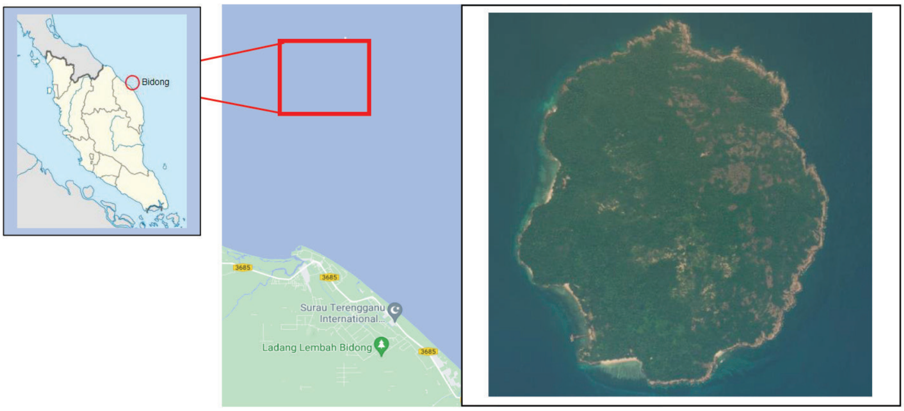

Figure 1: The study area of Pulau Bidong, Terengganu, Malaysia

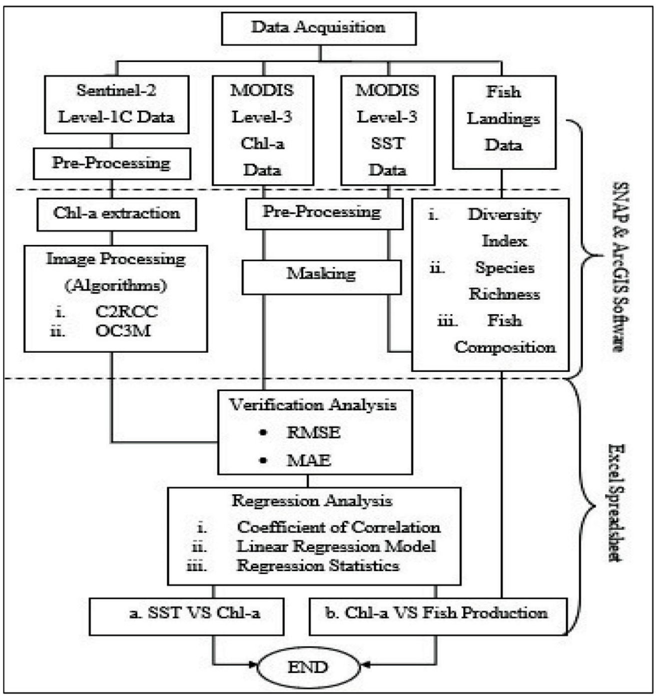

Figure 2: The flow of methodology

September 2016. These dates were selected to match the fish data collection date and due to limited daily data availability on the website. All the images were resampled to a 10 m resolution and cropped according to the study area in UTM/WGS 84 coordinates. MODIS Aqua Level-3 (Standard Map Image (SMI)) Chl-a concentration and SST data were downloaded from the Ocean Colour website. The Standard Map Image (SMI) of Chl-a with the resolution of 4 km for August 2015, September 2016 and a daily image of 3rd September 2016 were acquired for processing. The MODIS Aqua Level-3 Chl-a data were used as verification for Chl-a extraction from Sentinel 2 Level-1C using two algorithms, as well as in the regression analysis of the relationship between Chl-a, SST and fish diversity. The MODIS Aqua Level-3 of

August 2015 and September 2016 were acquired for study for SST. The SST and Chl-a data obtained was in 4 km resolution, orthorectified and cartographically gridded in UTM/WGS 84 coordinates.

Two software were used for data processing: The Sentinel Application Platform (SNAP) and ArcGIS is software that uses Geographical Information System (GIS) to perform digital mapping and information analysis. SNAP is all-in-one software that was developed by ESA to provide tools for raster data processing. The free software is equipped with various data processing tools such as Sentinel-1, Sentinel-2 and Sentinel-3.

Fish sampling data was obtained through trawling in the study area conducted in 2015 and 2016 to obtain the fish counts by weight. Six trawl lines were used and the data was obtained from the previous study by Mat Sulaiman and Ying (2015) through collaboration with the Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu. Figure 3 shows 11% of the 153 species found in 2015 and 44% were found in 2016. The remaining 45% of the species were found in both years.

Chl-a Extraction Estimation from Sentinel-2 MSI Images Using C2RCC Processor and OC3M Algorithm

The C2RCC processor, developed by Bowers, Md-Suffian and Mitchelson-Jacob (2012) was applied to the water layer to model the Chl-a estimation from the Sentinel imageries. The Neural Network models used by the processor

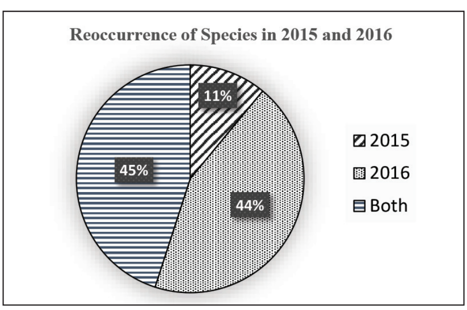

Figure 3: The reoccurrence of species in the Pulau Bidong coastal

computes its own atmospheric correction as well as provide results in the form of layers, which includes processing flags and uncertainties (Figure 4). The average values of temperature (29.2°C) and salinity (31.5) of the study area were used in the processing parameters (Bowers *et al*., 2012). Other parameters are set to default.

The second algorithm of OC3M is one of the most popular algorithms for Chl-a extraction that was developed for MERIS data and currently used as the basis of ocean colour processing for MODIS and Sentinel-3 Chl-a data. The algorithm uses three bands from the image with recommended reflectance of spectral ratio of remote sensing reflectance (Rrs443/Rrs551 and Rrs488/Rrs551. Bands 1, 2 and 3 (Blue to Green Bands) were used in this study to match the recommended reflectance values. The equation used is shown in Equation 1.

$$Log10\ (Chl) = a0 + a1*x + a2*x\text{^}2 + a3*x\text{^}3 + a4*x\text{^}4 \qquad (1)$$

where: x = Log10 (Rrs band ratio)

Accuracy Assessment Analysis of Estimated Chl-a

To analyse the accuracy of the Chl-a estimation results derived from the C2RCC and OC3M algorithms, statistical analysis of root mean square error (RMSE) and mean absolute error (MAE) was compared to observed data of MODIS Level-3 chlorophyll concentration. The comparison is made for only 3rd of September 2016 since other daily MODIS data for 10th, 20th August 2015 and 23rd September 2016 were missing so much data for comparisons. The data comparison was based on extraction points created along the trawling lines used for fish sampling (Table 1).

RMSE describes the standard deviation of the residuals. The RMSE is obtained by comparing the predicted values to calculated values where the results can range anywhere from 0 to 1. The lower the RMSE obtained, the better the result's accuracy (Equation 2).

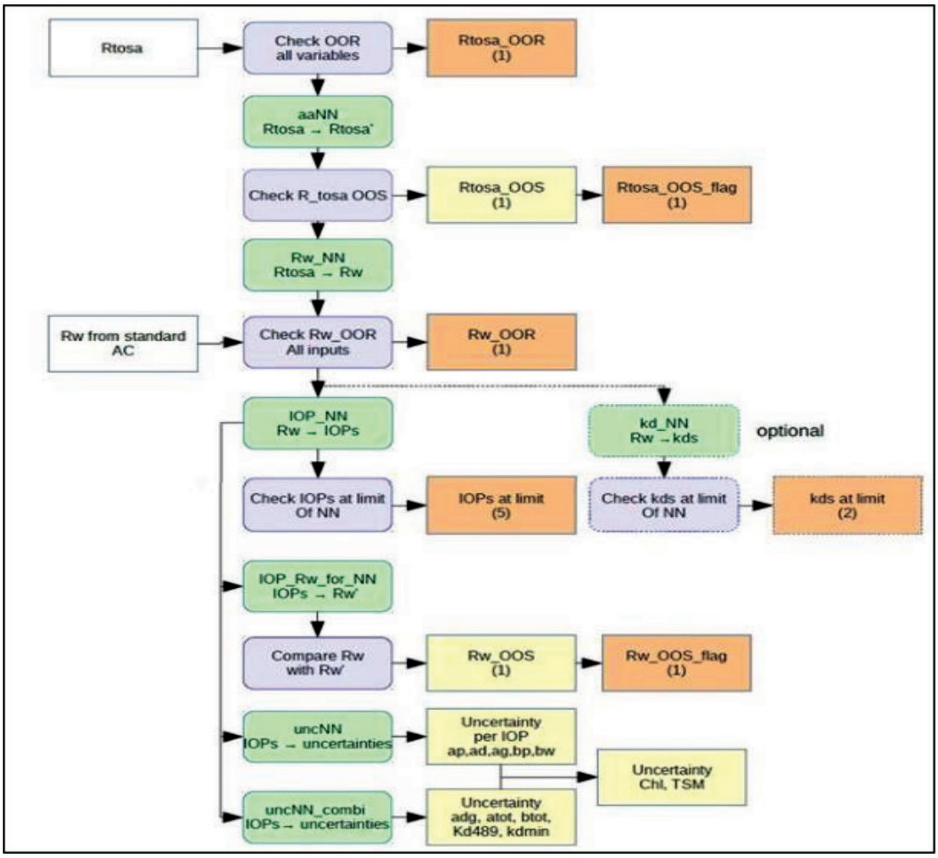

Figure 4: The processing model used by C2RCC processor
Source: Brockmann *et al*., 2016

Table 1: Coordinates of data extraction points along the fish trawling line

Extraction Points	Latitude	Longitude	Description
1	103^0 8' 15"	5^0 37' 50"	Line 1 ~ 2
2	103^0 7' 55"	5^0 37' 57"	Line 1 ~ 2
3	103^0 7' 57"	5^0 37' 40"	Line 1 ~ 2
4	103^0 7' 24"	5^0 37' 18"	Line 1 ~ 2
5	103^0 7' 57"	5^0 37' 05"	Line 1 ~ 2
6	103^0 8' 49"	5^0 37' 06"	Line 3 ~ 4
7	103^0 7' 39"	5^0 36' 52"	Line 3 ~ 4
8	103^0 7' 57"	5^0 37' 22"	Line 3 ~ 4
9	103^0 7' 40"	5^0 36' 35"	Line 3 ~ 4
10	103^0 8' 06"	5^0 36' 16"	Line 3 ~ 4
11	103^0 9' 22"	5^0 36' 22"	Line 5 ~ 6
12	103^0 7' 54"	5^0 36' 25"	Line 5 ~ 6

13	103^0 8' 13"	5^0 35' 56"	Line 5 ~ 6
14	103^0 8' 46"	5^0 35' 42"	Line 5 ~ 6
15	103^0 9' 55"	5^0 35' 38"	Line 7 ~ 8
16	103^0 8' 24"	5^0 35' 33"	Line 7 ~ 8
17	103^0 8' 09"	5^0 35' 59"	Line 7 ~ 8
18	103^0 10' 29"	5^0 34' 55"	Line 7 ~ 8
19	103^0 08' 45"	5^0 34' 55"	Line 7 ~ 8
20	103^0 09' 26"	5^0 35' 09"	Line 7 ~ 8
21	103^0 08' 39"	5^0 35' 06"	Line 9 ~ 10
22	103^0 08' 54"	5^0 34' 40"	Line 9 ~ 10
23	103^0 09' 18"	5^0 34' 38"	Line 9 ~ 10
24	103^0 10' 06"	5^0 34' 36"	Line 9 ~ 10
25	103^0 10' 47"	5^0 34' 02"	Line 9 ~ 10
26	103^0 09' 51"	5^0 33' 59"	Line 11 ~ 12
27	103^0 10' 24"	5^0 33' 21"	Line 11 ~ 12
28	103^0 11' 27"	5^0 33' 29"	Line 11 ~ 12

$$RMSE = \left[\sum_{i=1}^{N} \frac{(z_{fi}-z_{oi})^2}{N}\right]^{1/2} \quad (2)$$

where: Z = Value of the cell, N = Number of cell, i = Denotes particular layer

Absolute errors are the total errors that are found in the measured values. The absolute error can be calculated by deducting the measured value and the true value. The mean absolute error is the average of the absolute errors. It is commonly used to measure the accuracy of a continuous variable. The errors are calculated linearly meaning that all the errors are weighted equally in the average (Glen, 2016). MAE was calculated using the formula as shown below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_i - x| \quad (3)$$

where: n = Number of errors and $|x_i - x|$ = Absolute errors

Chl-a and SST Statistical Relationship Analysis

Coefficient of correlation, coefficient of determination and linear regression models are used to find the relationship between SST and Chl-a. The range of correlation coefficient values is $-1 \leq r \leq +1$. The correlation is close if $r \geq 0.7$ and $r \leq -0.7$ and the correlation is not close if $-0.7 < r < 0.7$. Higher "r" value indicates that the correlation is higher between the values. The sample correlation formula, which includes the covariance and standard deviations of the two factors are shown in Equations 4 and 5.

$$Covariance_{ij} = \frac{\sum_{k=1}^{N} (Z_{ik}-\mu_i)(Z_{jk}-\mu_j)}{N-1} \quad (4)$$

$$Correlation_{ij} = \frac{Covariance_{ij}}{\delta_i \delta_j} \quad (5)$$

where: Z = Value of the cell, μ = Mean of the layer, N = the number of cell, K = Denotes particular cell

Correlation of determination can be obtained by squaring the coefficient of correlation. It is used to measure the percentage of dependent values explained by independent values in a linear regression model (Pyrczak & Oh, 2019). The correlation of determination is used in this study to identify the extent of the Chl-a that is influenced by the SST.

$Determination_{ij} = (r)^2$ (6)

where: r = Coefficient of correlation

Determination of Relationship between Chl-a, Species Diversity, Composition and Richness

Species Diversity and Composition

From the trawling, the fish caught were sorted according to species and the weight and count of each species were recorded. From these values, the fish species diversity was calculated using the Shannon-Weaver Index developed in 1963 (Spellerberg & Fedor, 2003). The index takes both abundance and evenness into account in determining the diversity and richness of species. A high value of "H" will represent a more diverse range of species and vice versa. The Diversity Index is as follows:

Species Diversity (H) = $\sum^{n}_{i=1}$ pi ln pi (7)

pi = ni / N

where: ni = Number of individuals within species, N = Total number of individuals

The fish composition is determined by counts in which each species is given its percentage based on the total number of specimens collected. The percentage is used to measure changes in the volume of the same species between the years.

Margalef's Index was developed in 1958 is used to determine species richness based on the number of species and fish counts from sampling (Quindo *et al*., 2019). The index was applied to the collected data to determine species richness in the area for comparisons with Chl-a concentration values (Kamaruddin *et al*., 2011). The equation used is as follows:

Species Richness (D) = (S - 1) / (ln (N)) (8)

where: S = Total number of species, N = Total numbers of individuals in sample

The effects of Chl-a on fish diversity, composition and species richness were compared by a graph to visualize the trends of the variables between the two years.

Results and Discussion

Chl-a Concentration Estimation Using C2RCC Processor and OC3M in 2015 and 2016

Chl-a concentration obtained from the C2RCC processor for the study area in 2015 shows higher readings as compared to 2016. Table 2 shows the maximum Chl-a value of 56.8741 mg/m^{-3} while the minimum value was 0.0002 mg/m^{-3}. The average Chl-a value for 2015 is also highest with 0.7347 mg/m^{-3} as compared to 2016 at 0.1265 mg/m^{-3} (Table 2). Map obtained from this algorithm shows very little contrast in Chl-a concentration classes as the values are clustered around the lower concentrations thus making the map as a uniform green colour (lower values of Chl-a) map concentration (Figure 5).

OC3M results show a significantly different Chl-concentration content in the study area. The algorithm produced results with more consistent values. The highest recorded Chl-content was at 2.5449 mg/m $^{-3}$ with a difference of 54.3292 mg/m^{-3} as compared to the maximum value produced by the C2RCC algorithm. The average Chl-a is higher in 2015 compared to 2016, with values 0.5501 mg/m $^{-3}$ and 0.3621 mg/m^{-3}, respectively (Table 4). Classified and mapped using the same colour properties, the chlorophyll concentration from the OC3M algorithm shows a more even continuation between pixels where the values seem to transition smoothly instead of having harshly defined areas (Figure 6).

Table 2: Chlorophyll Concentration Statistics for C2RCC

Date	Average (mg/m^{-3})	Maximum (mg/m^{-3})	Median (mg/m^{-3})	Minimum (mg/m^{-3})	Sigma
10/8/2015	0.3136	41.9499	0.0841	0.0002	1.4877
20/8/2015	0.7347	56.8741	0.0570	0.0002	3.1414
3/9/2016	0.1264	33.2385	0.0999	0.0002	0.2386
23/9/2016	0.1265	24.2142	0.0971	0.0002	0.2503

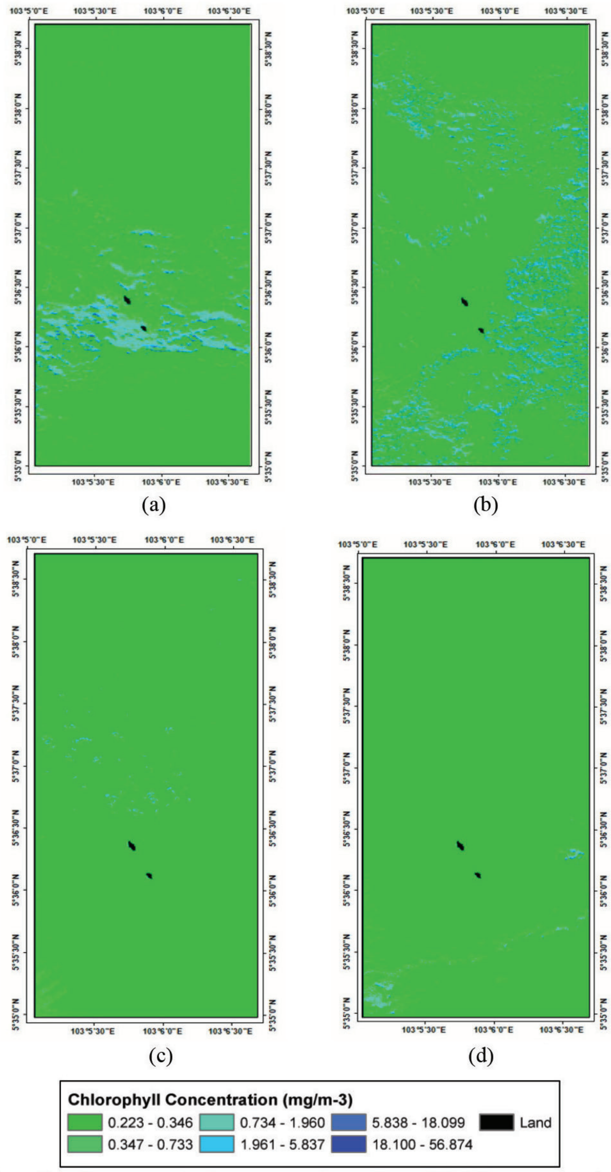

Figure 5: Chl-a estimation concentration map produces from C2RCC processor algorithm for: (a) 10/8/2015, (b) 20/8/2015, (c) 3/9/2016 and (d) 23/9/2016

Table 4: Chlorophyll concentration statistics for OC3M

Date	Average (mg/m^{-3})	Maximum (mg/m^{-3})	Median (mg/m^{-3})	Minimum (mg/m^{-3})	Sigma
10/8/2015	0.4201	1.4168	0.3938	0.2763	0.1238
20/8/2015	0.5501	2.5449	0.4439	0.1736	0.2377
3/9/2016	0.2735	1.9727	0.2663	0.1765	0.0592
23/9/2016	0.3621	1.7640	0.3576	0.302	0.0299

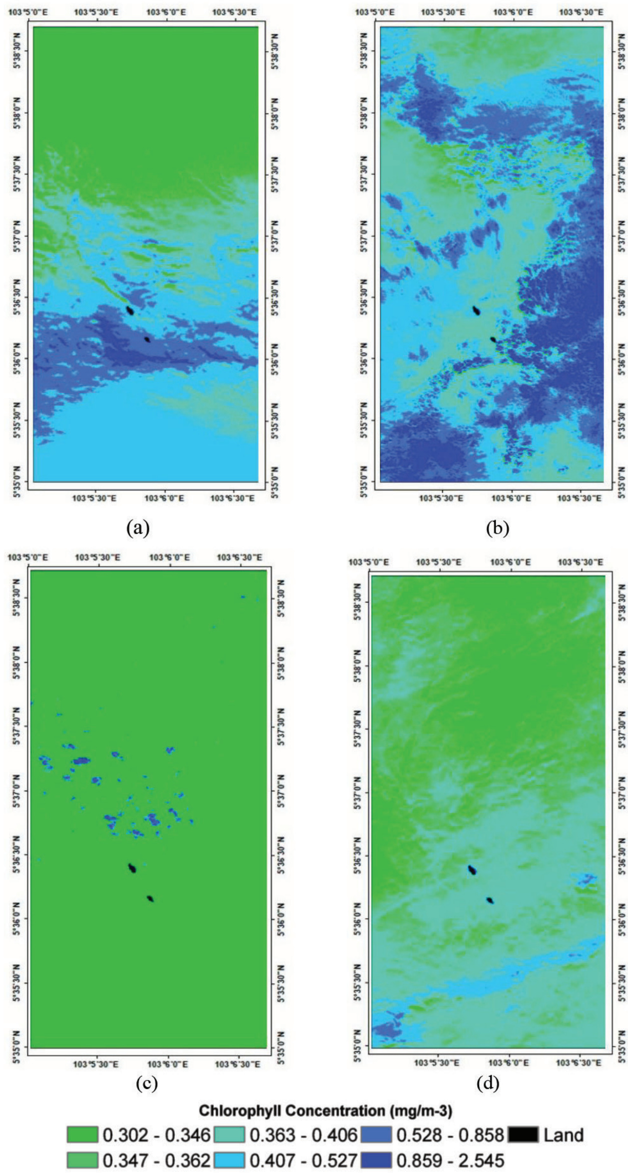

Figure 6: Chl-a estimation concentration map produces from OC3M algorithm for: (a) 10/8/2015, (b) 20/8/2015, (c) 3/9/2016 and (d) 23/9/2016

Accuracy Assessment of Chl-a Estimation Derived from Sentinel Data Using C2RCC and OC3M Algorithms with MODIS Data

To analyse the accuracy of estimated Chl-a results using the C2RCC and OC3M algorithms, the statistical analysis of RMSE and MAE were compared to observed data MODIS Aqua Level-3 chlorophyll concentration data. The result comparison was only made for 3rd of September 2016 since other daily MODIS data for 10th, 20th August 2015 and 23rd September 2016 contains too many no data/missing data for comparisons.

The comparison results in Table 5 show that the MODIS data values with the OC3M algorithm produces a lower RMSE of 0.05

while the C2RCC algorithm obtained an RMSE of 0.104. MAE obtained by the C2RCC algorithm was 0.097 while OC3M has a MAE of 0.049. Figure 5 indicated that Chl-a values from C2RCC tend to be inconsistent throughout the study areas, with a large range between the highest and lowest values while the OC3M and MODIS values are had a lower range between the largest and smallest values. Since lower RMSE and MAE values were quantified, therefore, the OC3M algorithm produces better chlorophyll concentration estimation compared to the C2RCC algorithm. The next analysis will focus on the relationship analysis between estimated Chl-a derived using OC3M with SST data from MODIS.

SST and Chl-a Relationship Analysis for Pulau Bidong between 2015 and 2016 Using OC3M, MODIS Chl-a and MODIS SST

SST is known to has an impact on water chlorophyll content. Higher SST is often associated with a lower Chl-a value, hence, through linear regression, Chl-a concentration for data extraction points derived from both MODIS Level-3 data and OC3M algorithm can be compared to the MODIS SST to validate the theory. Observed Chl-a concentration and SST values at extraction points for August 2015 and September 2016 are taken from MODIS data. MODIS Level-3 data are processed with the aid of in-situ data, hence, the values from these data are more reliable to show the difference between Chl-a and SST from the two years. Figure 7 shows the Chl-a concentration in August 2015 was higher than September 2016. The maximum Chl-a recorded for the study area was 0.558 mg/m^{-3}. Average Chl-a value for 2015 was 0.392 mg/m^{-3} while in 2016 the average was 0.276 mg/m^{-3}. This shows that the average Chl-a for the area reduced by 30% from 2015 to 2016. The minimum value for Chl-a recorded was 0.224 mg/m^{-3}.

For the changes in SST, 2016 showed a significantly higher SST than 2015. Figure 8 shows the SST in August 2015 was significantly lower than September 2016 at an average of 30.5°C. The highest recorded temperature was at 31.4°C and the lowest was at 30.2°C. The range of differences in SST are not as significant as the

Table 5: Root Mean Square Error and Mean Absolute Error of C2RCC and OC3M

RMSE C2RCC	RMSE OC3M	MAE C2RCC	MAE OC3M
0.104	0.050	0.097	0.049

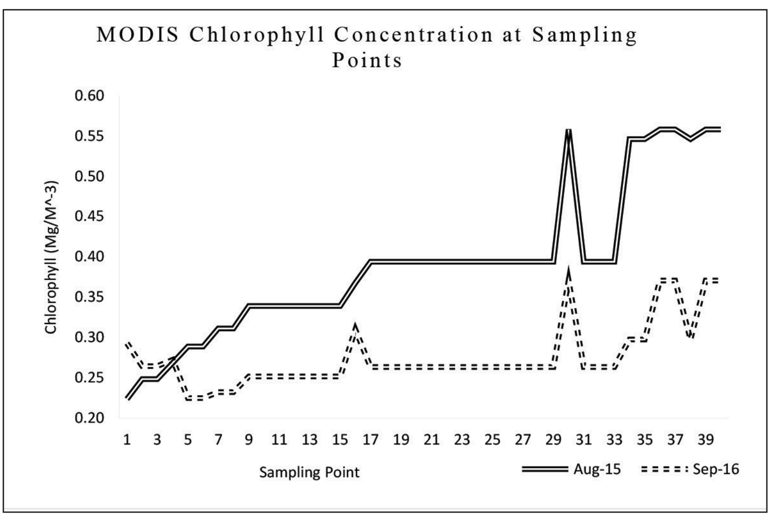

Figure 7: MODIS chlorophyll at sampling points

difference in Chl-a values. From these data, it is observed that the higher temperature in 2016 results in a lower Chl-a values for the year. The effects of SST on Chl-a can be clearly seen in extraction points 1 to 9 where the values of SST and Chl-a are at the opposite ends of the graph. The higher Chl-a concentration in 2015 is also seen to be influenced by the SST. This analysis will be further validated using regression models in the following sections.

Average values of Chl-a by MODIS and OC3M algorithm for the months August 2015 and September 2016 were compared to MODIS SST monthly average data for the same months. Linear regression models were used to identify the correlation between the two values. The results for 2015 MODIS Chl-a and SST correlation show that there is a weak negative correlation of -0.1509 between the values (Table 6). The coefficient of determination was 2.3%, indicating only 2.3% of the Chl-a values correlate with the SST values (Figure 9). Meanwhile, OC3M Chl-a and SST regression model for 2015 also shows low correlation between the two values at -0.2687. The coefficient of determination (R^2) was only 0.07, which means that only 7% of the Chl-a values are explained by the SST.

The results of regression analysis for MODIS Chl-a and SST in September 2016 show the correlation coefficient (Multiple R) at -0.062, which is a weak negative relationship between the two values (Figure 10). The coefficient of determination for the process was 0.004 indicating that only 0.4% of the values fit the regression analysis model (Table 7). The standard error for the model was 0.045.

Average values of Chl-a by OC3M algorithm for September 2016 was compared to MODIS monthly SST average data of the same month. The results show a weak negative correlation of -0.1229. The coefficient of determination (R^2) was only 0.0151, which means that only 1.5% of the Chl-a value are explained by the SST (Figure 11 and Table 8).

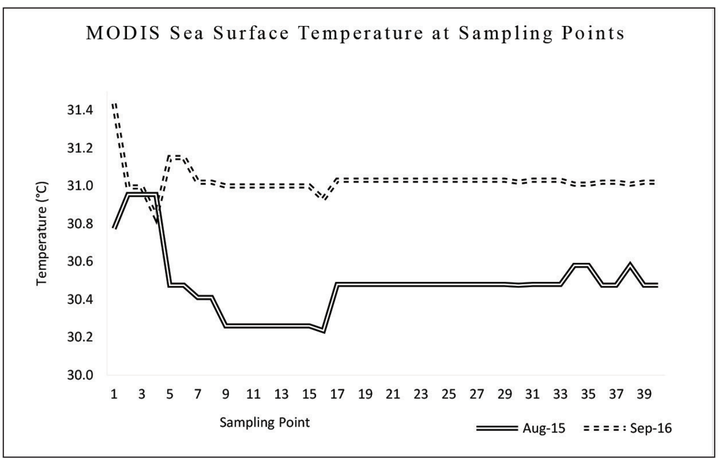

Figure 8: MODIS SST at sampling points

Table 6: Regression Statistics for MODIS Chl-a and MODIS SST 2015

Regression Statistics	
Multiple R (Coefficient of correlation)	-0.1509
R Square (Coefficient of determination)	0.0228
Adjusted R square	-0.0017
Standard error	0.0990

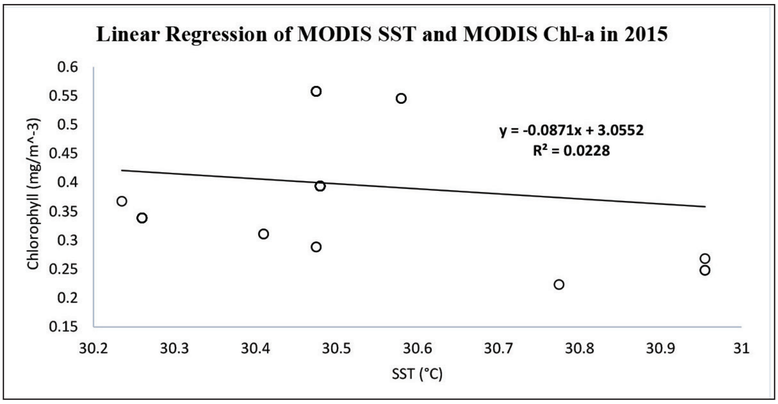

Figure 9: Linear regression model of MODIS Chl-a and MODIS SST for year 2015

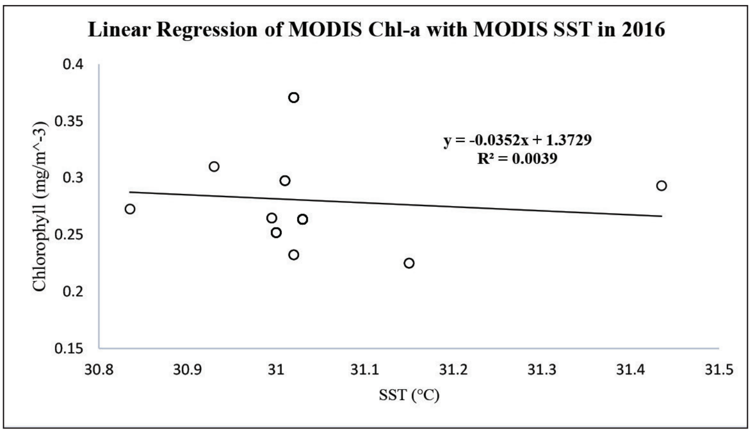

Figure 10: Linear regression model of MODIS Chl-a and MODIS SST for year 2016

Table 7: Regression statistics for MODIS Chl-a and MODIS SST 2016

Regression Statistics	
Multiple R (Coefficient of correlation)	-0.0622
R Square (Coefficient of determination)	0.0039
Adjusted R square	-0.0210
Standard error	0.0448

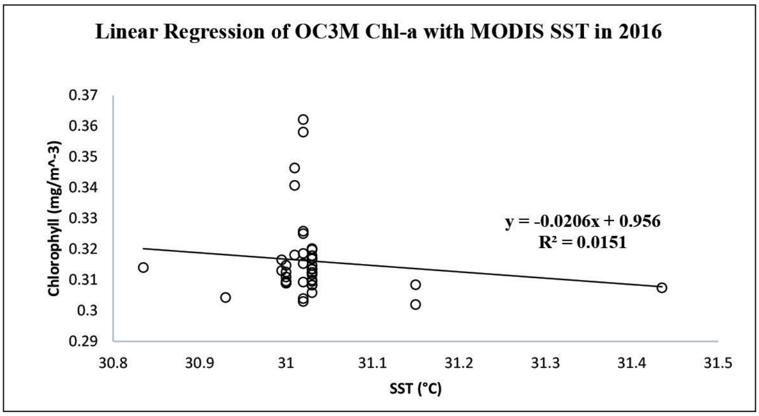

Figure 11: Linear regression of OC3M Chl-a and MODIS SST for year 2016

Table 8: Regression statistics for OC3M Chl-a and MODIS SST 2016

Regression Statistics	
Multiple R (Coefficient of correlation)	-0.1229
R Square (Coefficient of determination)	0.0151
Adjusted R square	-0.0095
Standard error	0.0132

Relationship between Chlorophyll Concentration, Fish Species Diversity, Composition and Richness

To analyse the relationship between Chl-a and fish production in the study area, fish diversity and composition were used. Fish data collected by trawling was from a study by Mat Sulaiman and Ying (2017) where the diversity, species richness and species evenness index were computed using Shannon-Wiener diversity H′(log 2) method. They were 153 fish species found in the area: 83 species were recorded in 2015 and 134 species were recorded in 2016. The fish diversity index in 2016 was 2.279 and 0.378 in 2015 (Table 9). The fish richness index increased from 8.018 to 13.731 in 2016. Species evenness, a measure of the biodiversity of the area, also increased in 2016.

Comparison of the diversity index and chlorophyll concentration from both MODIS and OC3M algorithm between the years shows negative correlation between the two values. In 2015, a higher Chl-a average of 0.399 and 0.483 was recorded with a diversity index reading of 0.378. The average Chl-a was 0.281 and 0.316 in 2016, with an index of 2.279. Higher species variety in 2016 resulted in a higher species richness index of 13.731 for the year while 2015 obtained an index of 8.018. Figure 12 indicated that the Chl-a values does not affect the diversity of species in the area.

Table 9: The diversity, species richness and species evenness index

Year	Species	Diversity Index	Species Richness	Species Evenness
2015	83	0.378	8.018	0.086
2016	134	2.279	13.731	0.465

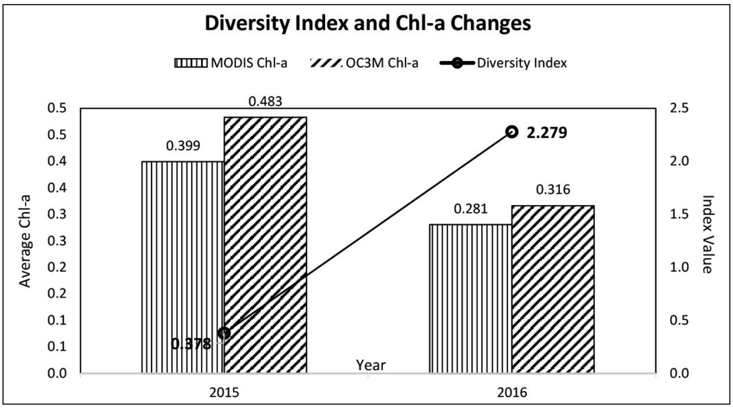

Figure 12: The diversity index and chlorophyll changes from year 2015 to 2016

Discussion

The results from C2RCC and OC3M algorithms showed disparate Chl-a concentration ranges from the Sentinel data. C2RCC produced mostly an underestimated Chl-a concentration with a few overestimated values when compared to the MODIS Chl-a data. The range of Chl-a obtained from the algorithm also shows a soaring range, which is usually rare in waters in the same area since there were no extreme climate conditions or pollution that can create a drastic difference between the values in the study area. The OC3M algorithm on the other hand, obtained results with a consistent Chl-a concentration and have a smaller range of values.

Accuracy assessment results showed that OC3M produced a better RMSE and MAE than C2RCC as compared to MODIS Chl-a. However, the algorithm tends to overestimate the Chl-a in the area as compared the MODIS Chl-a. Similar overestimation of Chl-a were found by Tan *et al*. (2006), Moses *et al.* (2009) and Lah *et al*. (2014) due to low spatial resolution and high nutrient input discharged from the rivers. Is it found that C2RCC algorithm may not be suitable for the chlorophyll estimation in the study area because the algorithm is suitable for highly turbid and eutrophic waters (Ridzuan *et al*., 2020). These water conditions are unlike that of Bidon Island's, which is clearer and receives minimum discharge from the rivers since the island is 50 km away from the Marang Jetty on the Terengganu mainland.

Other factors that can contribute to the poor extraction of C2RCC include setting of the processing parameters and the selection of masks used for the processing. The different resolution between the validation data and processed data (i.e., 4 km and 10 m resolutions) may also be one of the reasons that both algorithms scored poor RMSE and MAE. Furthermore, OC3M algorithm provides reliable result since it efficiently estimated in clear or more oceanic water, where optical properties and bottom reflectance is negligible (Sun *et al*., 2010; Ridzuan *et al*., 2020).

Chl-a concentration and SST value regression analysis results show that there is very low correlation between these two variables, indicating that SST variation has a small effect on Chl-a concentration. Through the analysis of Chl-a and SST changes from 2015 to 2016, this correlation can be seen clearly, even so, the regression models reveal contrary results (Table 10).

The correlation coefficient score obtained by MODIS and OC3M shows that there is a weak negative correlation between the values. This means that an increase in SST will result in a decrease in Chl-a values. The highest coefficient of determination was obtained by OC3M in 2015 with only 7.5% of the Chl-a

Table 10: Summary of regression for MODIS and OC3M Chl-a with MODIS SST

	Correlation of Coefficient (r)		Coefficient of Determination (R^2)		Standard Error	
Year	**MODIS**	**OC3M**	**MODIS**	**OC3M**	**MODIS**	**OC3M**
2015	-0.1509	-0.2687	2.28%	7.2%	0.0990	0.0781
2016	-0.0622	-0.1229	0.39%	1.5%	0.0448	0.0132

data influenced by SST. From this, it is found that Chl-a in the area is very weakly influenced by SST. The is unexpected since the changes in Chl-a and SST mentioned before had a different trend. With standard errors as low as 0.01, the possibility of error in the linear regression can be ruled out, as a low error indicates higher precision of the regression model. Similar negative relationship was also found by Ji *et al*. (2018) for the southeast East China Sea with the mean correlation coefficient of -0.4999 for an average temperature of 22.81°C, probably due to the low nutrient concentration or the excessive temperature inhibiting the growth of phytoplankton. The low correlation between Chl-a and SST in the study area may be caused by factors such as the different spatial resolution of satellite sensors during capture of the images with MODIS at 4 km and Sentinel at 10 m and also the influence of cloud cover. The findings reveal that fish diversity in the area was not influenced by the Chl-a concentration. The fish diversity index obtained in 2016 was higher than in 2015 even though the average Chl-a concentration was lower for the year. The huge gap between fish diversity may be explained by the catch made each year. In 2015, only 102 kg of fish were caught by trawling for analysis while the catch for 2016 was 443 kg. This makes the assessment uneven as the catch weight more than double in 2016. The larger catch may be why the species recorded were significantly more in 2016.

Species composition in the area shows that with higher diversity, the fewer individuals of the main species were found. Although the diversity index between these years is significantly different, the individual counts of each species were higher in 2015, especially for the dominant species of *Leiognathidae* (Ponyfish). Generally, ponyfish move in large schools on the seabed, nibbling the sediment in search of benthic organisms (Seah *et al*., 2009). The number of individual fish in 2015 was the highest with 27,656 individuals. Meanwhile, in 2016, the number of individuals was lower with 16,089. It can be assumed that this increase in the number of individual of fish was caused by the competition for food (phytoplankton) in the area since 2015 has a higher Chl-a average with lower diversity index and 2016 has a lower Chl-a with higher diversity index. Seah *et al*. (2009) stated that the orangefin ponyfish, *Photopectoralis bindus* can be categorized as bentho-pelagic feeders that have forwardly mouth types and feed mainly on zooplankton and zoobenthos. As the basis of aquatic food webs, phytoplankton are consumed by primary consumers such as zooplankton, small fish and crustaceans. Abo-Taleb (2019) stated that plankton play a crucial role in influencing fluctuations in the naturalistic survival rates of juvenile, larval fish and adult fish stock.

The fish diversity, community structure and species community are interdependent on many abiotic and biotic factors such as availability of food, breeding sites, water current, depth, topography and physical characteristics of water (Harris, 1995). Another reason, this may be the sedimentation from sand to rocky creating a greater variety of habitats that support more fish species. Beena *et al*. (2016) mentioned that the altered habitat is home to fewer fish species, but the variety habitat supports a greater diversity.

Conclusion

The research achieved its aim of determining the relationship of sea surface temperature and chlorophyll concentration as well as its effect on fish diversity around Bidong Island, Terengganu. Through the validation of chlorophyll contents obtained from C2RCC and OC3M algorithms, it can be concluded that C2RCC is not suitable for the open waters of Pulau Bidong due to the large RMSE and MAE obtained when compared to MODIS Chl-a data. It is found that OC3M produces a better result from the Sentinel data, with acceptable RMSE and MAE. The validation of these algorithms with MODIS Chl-a also shows that the OC3M algorithm tends to overestimate the Chl-a in the area. Several factors that can affect the quality of the processing are ruled out, including the parameters used, cloud coverage, sensing errors and data quality.

Regression analysis to determine the correlation between Chl-a and SST showed a weak negative correlation between the values for both years. This proves that the Chl-a in the study area is not directly affected by SST changes. Although the model has high accuracy, this result may not be as accurate due to different spatial resolutions. This is a common problem when in-situ data is not available and sensing data from MODIS also has its limits, especially in the resolution and the amount of data generalization (monthly composite).

Fish variability in the area was also not be affected by the chlorophyll content as found in this research. However, the fish composition is seen to reduce with the increase of species richness and diversity. The analysis shows that the Chl-a readings in 2016 might be lower than Chl-a readings in 2015 due to higher fish composition and diversity in the area. This can be explained since the larger number of fish in the ocean will create more competition for food source (phytoplanktons). Since phytoplanktons are measured from Chl-a, it is safe to assume that higher fish diversity and species richness will result in lower water chlorophyll content in an area.

The overall findings show that Chl-a is not only affected solely by SST. Chl-a content in an area can also be influenced by the characteristics of its surrounding water and biodiversity. The use of C2RCC and OC3M algorithm on Sentinel-2 MSI images produces a moderately accurate result, with OC3M being better than the C2RCC algorithm. The extent of these factors affecting each other can be further studied with in-depth utilization of different algorithms as well as extensive data collection for a better result.

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