SPATIAL VARIABILITY ASSESSMENT OF LOCAL CHLOROPHYLL-A ESTIMATION USING SATELLITE DATA

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To my family, especially my beloved husband and son

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ABSTRACT

The estimation of Chlorophyll-a (Chl-a) for optically complex water from satellite is challenging. Moderate Resolution Imaging Spectroradiometer (MODIS) is an ocean colour satellite which has low spatial resolution and this has led to bias estimate and scale effect that eventually induced errors in Chl-a retrieval using local ocean colour algorithm. Studies on Chl-a variation, assessment of MODIS data and development of local ocean colour algorithm are less for Malacca Straits water. The aim of this study is to locally calibrate and validate the Chl-a derived from MODIS standard Chl-a algorithm (OC3M) on the latest R2013 data within the acceptable error tolerance at the Absolute Percentage Difference (APD) below 35% and to test the algorithm's applicability. Iterative regression method with weighted function (WFd) namely Iterative Conditional Regression Model (ICRM) is introduced to reduce the spatial bias in the Chl-a estimate. Locally calibrated OC3M algorithm with in-situ data taken at two static stations and kernel 7×7 size named as OCms1 (calibrated with in-situ Case-1 water) and OCms2 (calibrated with in-situ Case-2 water) remarkably reduced the Chl-a bias with APD of 37% and 30% from 54% and 116% respectively. Then, using the ICRM, the APD of OCms1 WFd and OCms2 WFd is 26% and 29% respectively. Results of OCms WFd and OCms (with and without weighted function respectively) are combined for mapping the Chl-a in Case-1 and Case-2 waters. Result of applicability test and statistical analysis shows that OCms WFd ocean colour algorithm provides statistically highest accuracy for Chl-a estimation. The development of local Chl-a algorithm is essential for accurate Chl-a retrieval and it is significant to other marine studies such as in primary production and algal bloom in Malacca Strait water.

ABSTRAK

Anggaran klorofil-a (Chl-a) untuk perairan yang kompleks secara optikal daripada satelit adalah mencabar. Pengimejan spectroradiometer resolusi sederhana (MODIS) adalah satelit warna lautan yang mempunyai resolusi spatial yang rendah dan membawa kepada anggaran bias dan kesan skala yang akan memberi ralat dalam dapatan Chl-a dengan menggunakan algoritma warna lautan tempatan. Kajian mengenai variasi Chl-a, penilaian data MODIS dan pembangunan algoritma warna lautan tempatan adalah kurang untuk kawasan perairan Selat Melaka. Tujuan kajian ini adalah untuk membuat kalibrasi tempatan dan pengesahsahihan Chl-a yang diperolehi daripada algoritma Chl-a piawaian MODIS (OC3M) ke atas data R2013 yang terkini dengan toleransi ralat yang diterima pada perbezaan peratusan mutlak (APD) di bawah 35% dan untuk menguji kebolehgunaan algoritma tersebut. Kaedah regresi secara lelaran dengan fungsi pemberat spatial (WFd) iaitu Model Regresi Lelaran Bersyarat (ICRM) diperkenalkan untuk mengurangkan bias spatial dalam anggaran Chl-a. Algoritma OC3M yang dikalibrasi secara tempatan dengan data lapangan yang diambil pada dua stesen cerapan statik dan saiz tetingkap 7x7 yang dinamakan sebagai OCms1 (dikalibrasi dengan data lapangan untuk perairan Kes-1) dan OCms2 (dikalibrasi dengan data lapangan untuk perairan Kes-2) telah mengurangkan bias Chl-a dengan ketara sebanyak 37% dan 30% daripada 54% dan 116%. Seterusnya dengan menggunakan ICRM, APD untuk OCms1 WFd dan OCms2 WFd adalah masing-masing 26% dan 29%. Keputusan OCms WFd dan OCms (dengan fungsi pemberat dan sebaliknya) digabungkan untuk memetakan Chl-a bagi perairan Kes-1 dan Kes-2. Keputusan untuk ujian kebolehgunaan dan analisis statistik menunjukkan algoritma warna lautan OCms WFd memberi ketepatan yang tinggi secara statistik untuk penganggaran Chl-a. Pembangunan algoritma Chl-a tempatan adalah penting untuk memperoleh Chl-a yang tepat dan boleh digunakan dalam kajian lautan yang lain seperti produktiviti primer dan letusan alga di perairan Selat Melaka.

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LIST OF ABBREVIATION

APD	Mean absolute percentage difference
BNO	Bagan Nakhoda Omar
Cal/Val	Calibration and Validation
Chl-a	Chlorophyll-a
CDOM	Colored dissolved organic matter
CI	Confidence Interval
CZCS	Coastal Zone Colour Scanner
EMR	Electromagnetic radiation
Gof	Goodness of fit
ICRM	Iterative Conditional Regression Model
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Radiometer
MBR	Maximum Band Ratio
NASA	National Aeronautics and Space Administration
NIR	Near infrared
R_{rs}	Remote sensing reflectance
RPD	Relative percentage difference
RMSE	Root mean square error

ST1	Station 1
ST2	Station 2
SeaDAS	SeaWiFS Data Analysis System
SeaWiFS	Sea-Viewing Wide Field-of-View Sensor
SSE	Sum of Squares Error
TSS	Total suspended sediment
VIIRS	Visible and Infrared Imager/Radiometer Suite

LIST OF SYMBOLS

a	Absorption
a_T	Total absorption coefficient
b_b	Backscatter
b_{bT}	Total backscatter coefficient
C_a	Chlorophyll concentration
L_w	water-leaving radiance
Chl_{ret}	Chl-a retrieved by the Chl-a algorithms
Chl_{is}	In situ Chl-a
nL_w	Normalized water-leaving radiance
R_{rs}	Remote Sensing reflectance
$\mathrm{R}_{3\mathrm{M}}$	Maximum 3 band ratio
λ	Wavelength

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Phytoplankton is a marine photosynthetic microorganisms formed by the green biomass called chlorophyll-a (Chl-a) which is the primary molecule of chlorophyll pigment and responsible for the photosynthesis process. Phytoplankton plays major role in the oceanic food chain and has become the oxygen production agent to ocean bio-creatures and the environment regulator in the ocean carbon cycle. Phytoplankton intrinsically helps to regulate the world climate and by knowing the spatial and temporal attributes would improve understanding of its influences to the world climate pattern. Measuring phytoplankton in the ocean is literally a tedious and complicated practice. However, by the advancement of satellite remote sensing the phytoplankton estimation is plausible thanks to spectroscopic measurement, through that the Chl-a optical properties can be determined as a function of the absorption and scattering representing the magnitude of concentration and spatio-temporal distribution of phytoplankton abundant. In fact the optical properties variant provide synoptic and continuous mapping of Chl-a at promising resolution in time and space.

Optically sensing Chl-a applies the electromagnetic radiance (EMR) to define the colour or spectral related feature of Chl-a in the bio-optical model and this application literally known as ocean colour remote sensing is very prevalent in marine biological research. Satellite based ocean colour bio-optical model has evolved to cope with different mapping scales and various ocean climate and as a result, different algorithm and application have been demonstrated. Remote sensing image is composed of pixels representing the water optical properties that geometrically registered to earth coordinates. To estimate the remotely sensed Chl-a, two ocean colour model have been devised. First, the empirical model in which statistical regression is applied between sea truth Chl-a and satellite derived apparent optical properties (AOP) (e.g, the remote sensing reflectance, R_{rs}) by assuring both measurements are highly correlated in time and space. The most favourable empirical model depends on the spectral bands (typically by blue and green bands) and the water types (Case-1 and Case-2 water). Secondly is the analytical model which based on the inversion of a forward radiance model. Other than that, integration of both modelling schema was also devised (known as semi-analytical model) but requires theoretical AOP estimation optimized by in-situ inherent optical properties (IOP) (all definition of AOP and IOP are described in the glossary). The present thesis discusses on the application of empirical model to estimate the Chl-a due to the fact this model is straightforward and no dependent to ocean and geophysical parameters but completely dependent to satellite remote sensing products..

To study potential of the empirical model in Chl-a estimation, Malacca Strait is chosen in this thesis. Malacca Strait is one of the marginal seas in the Peninsular Malaysia and has significant value to Peninsular Malaysia as one of the productive fishing grounds (692,985 metric tons of fishes which valued at RM2.263 billion per year) as reported by Kasmin (2010) and the prominent ocean trade network in the Silk Road. This area is surrounded by different water types, receiving continuous water disposal from the major river outlets and experiencing distinctive seasonal climate every year which make it the best ocean water to examine the quality of satellite derived Chl-a by empirical model and assses the impact of spatial variation.

1.2 Background of Study

Optical satellite remote sensing basically equipped by passive sensor to observe all reflected and emitted EMR coming from the ocean surface at visible to near infra-red (NIR) wavelength. The NASA Earth Observation System (EOS) program has commissioned series of passive ocean colour remote sensing in space such as Coastal Zone Colour Scanner (CZCS) (Gordon *et al.*, 1980); Sea-Viewing Wide Field-of-View Sensor (SeaWIFS) (Hooker *et al.*, 2000); Moderate Resolution Imaging Spectroradiometer (MODIS) (Esaias *et al.*, 1998); Visible and Infrared Imager/Radiometer Suite (VIIRS) (Feldman, 2015), and Medium Resolution Imaging Spectrometer (MERIS) (Le *et al.*, 2013). Amongst them, MODIS is currently the most distinctive ocean colour mapping sensor that provides continuous, long-term and the most reliable Chl-a related products for ocean and atmospheric studies in the last decade. Prior to MODIS mision, the SeaWiFS brought 8 spectral bands ranging from 412 to 865 nm to collect global optical data at 4 km spatial resolution but the mission was completely shut down in 2010. MODIS offers 36 spectral bands at higher spatial resolution of 1km. The spectral bandwidth is narrower and more sensitive to the variation of bio-optical signatures because of the signal-to-noise ratio (SNR) is 2-4 times higher than the SeaWiFS (Hu *et al.*, 2012). The recent MODIS data taken by Aqua platform (hereafter denoted as MODISA) has been released since 2013 (R2013 version) and the quality is greater owing to the higher SNR derived from the in-depth radiometric correction at band 8 and 9 (412 and 413nm respectively) (Feldman, 2014). However, it has yet a study that demonstrates the impact of using MODISA R2013 data for the Chl-a estimation in Malacca Strait.

Ocean colour retrieval algorithm is specifically designed either for Case-1 or Case-2 water in bio-optical model, (Morel & Prieur, 1977). The Case-1 water has the water optical properties that are mainly induced by the phytoplankton and the co-varying in-water constituents. For the Case-2 water, the water optical properties are relatively more dominated by other non-co-varying in-water constituents either in the form of organic or inorganic particles than the phytoplankton. The empirical Chl-a estimation is complicated to be applied simultaneously for Case-1 and Case-2 that leads to inherent bias. In case of Malacca Strait, different water types would exist in a field-of-view (FOV) of EOS ocean color satellite representing Chl-a in a single pixel because in 1km x 1km areal pixel there are active nutrient rich sediment discharge from the nearby river outlets and continuous upwelling and downwelling currents from various depth variation at near and off the coast that diversified the ocean salinity and temperature rate.

Technically, correlated satellite derived Chl-a is based on the concept of ratio of the remote sensing reflectance at blue to green band (Tassan, 1981). This rationale lies on the fact that the photosynthetic pigment of Chl-a absorbs much blue and red radiance than of the green and reflects much radiance in blue to green. The hypothesis is that band ratio increases as the amount of the Chl-a abundant being sensed is higher. Though, the band ratio sometimes impaired by the lower band ratio value (*i.e.*, in the case of 443/555 nm) when the higher Chl-a abundant escalates the R_{rs} at 555nm (Lee & Carder, 2000; Martin, 2014). Therefore, the maximum band ratio (MBR) is introduced and taking advantage of significant SNR remains as high as possible even over a broad range of Chl-a concentration. The above mentioned band ratio methods completely rely on the R_{rs} at different ocean color bands (Dierssen, 2010) and this has proved that two bands (OC2), three bands (OC3) and four bands (OC4) have been applied in EOS missions. In the present thesis, three ocean color bands was used in MODIS Chl-a estimation and commonly known as OC3M. The significant usage of OC2, OC3 or OC4 was discussed thoroughly in O'Reilly *et al.* (1998). To date, there are other latest empirical algorithm have been devised such as color index (CI) (Hu *et al.*, 2012), normalized difference chlorophyll index (NDCI) (Mishra & Mishra, 2012), and semi-analytical algorithm (SAM_LT) (Pieri *et al.*, 2015), however, those variants are mainly introduced to optimize the typical band ratio algorithm for estimating Chl-a concentration in oligotrophic water and turbid water area in low Chl-a concentration (below 1 mm^3/mg).

Empirical Chl-a algorithms such as OC4v4 and OC3M devised for SeaWiFS and MODIS respectively have been proved as the global Chl-a algorithm. Though, the satellite derived Chl-a may differ if these algorithms are applied locally (within 1 pixel or 9 pixels) or regionally (more than 9 pixels) because the Chl-a diversity in the ocean is exceptionally dynamic. It is a need to calibrate and thus validate the global Chl-a algorithm by downscaling the Chl-a at local scale which have been done by several studies (Cannizzaro & Carder, 2006; Lee & Hu, 2006; Le *et al.*, 2013). The OC3M algorithm was designed to estimate the Chl-a for Case-1 water and this would yield misleading Chl-a if it was applied in Case-2 water (Gordon & Clark, 1981; Moses *et al.*, 2009; Yang *et al.*, 2010). Calibration and validation exercise (Cal/Val) is therefore compulsary to apply on the satellite derived Chl-a in all cases of water as long as the absolute percentage difference (APD) is less than 35% (accuracy set by the NASA). However, this accuracy is nearly hard to achieve on OC3M and SeaWiFS OC4v4 algorithm particularly for Case-2 water (Esaias *et al.*, 1998; Darecki & Stramski, 2004; Volpe *et al.*, 2007).

The Asian monsoon strongly influences the spatial distribution of Chl-a in Malacca Strait and satellite observation has proved as the most practical tool to measure the impact (Tan *et al.*, 2006). Interannual Chl-a variation in the northern, middle and southern part of Malacca Strait was majorly associated with the El-Nino/Southern Oscillation (ENSO) and river runoff as reported in (Siswanto & Tanaka, 2014). The study shows that the Chl-a variation was influenced by the north-east (December to January) and south-west (May to August) monsoon however the impact of local Chl-a algorithm towards spatial variability was not presented.

1.3 Problem Statement

Based on the background study, issues of this study can be drawn as follows:

1. Studies by Ab.Lah *et al.* (2014) and Darecki (2004) on proved that the MODISA empirical Chl-a algorithm (OC3M) exhibits fairly acceptable Chl-a estimates with the APD <= 35% for off coast (mostly by Case-1 water) but higher (APD >90%) near the coast water (probably by Case-2 water). By the recent MODISA R2013 data released, the empirical Chl-a estimation can be improved and performed at local scale. To date no study has been locally

conducted to test applicability and accuracy of the R2013 on the Strait Malacca water.

2. MODIS pixel that matchs up with the corresponding in-situ point is needed for the empirical OC3M algorithm. To perform the pixel matching, different kernel window (starting from 3x3 kernel) is possible to use. Yet, size of kernel is limited because the Chl-a representing in the pixel varies with the corresponding in-situ Chl-a. Pixel averaging is commonly practiced but this would lead to spatial bias as the Chl-a concentration is fairly homogeneous within the 0.1 m^2 water column and it is arguable to compare the averaged MODIS Chl-a concentration of one pixel in approximate 1 km^2 water column. In this case, the spatial variability impact may reduce the correlation of OC3M with the in-situ (Chen *et al.*, 2013).

3. Calibration and validation exercise (Cal/Val) requires at least 30 match-up samples (to achieve normal distribution) that are sparsely located in the study area. Yet, match-up samples are located at two independent in-situ stations where continuous daily Chl-a was measured in this study. No study was conducted to assess the spatial impact on Cal/Val by means of static sample.

1.4 Research Objectives

The aim of this study is to calibrate and validate the Chl-a derived from empirical Chl-a model using the latest reprocessed MODISA R2013 data for Malacca Straits. The objectives are the followings;

1. To develop local empirical model for estimating satellite derived Chl-a over Malacca Strait by means of MODISA R2013 data and global OC3M;

2. To compare the performance of local Chl-a estimation using MODISA R2010 and R2013 data;

3. To assess the impact of spatial variability on local Chl-a algorithm by means of the estimation accuracy in different kernel window size and distance of pixel to in-situ point; and

4. To test the applicability of the new calibrated Chl-a algorithm in the Malacca Strait water in regard to the impact of seasonal monsoon, coastal outputs and precipitation.

1.5 Significant of Study

Retrieving accurate Chl-a estimate by using remote sensing over Malacca Strait water is worthwhile as this technique conveys reliable information of phytoplankton and nutrient at larger scale and faster acquisition. Synoptic Chl-a mapping implies the intensity distribution and origins of nutrient along the coast of Peninsular Malaysia and Sumatra Indonesia. Massive suspended sediment loading from rivers outlets in Peninsular Malaysia and Sumatra that caused variation of phytoplankton can be determined by map of Chl-a concentration derived from this study. Information of nutrient is essential to determine the degree of marine biological production in Malacca Strait. All these marine substances significantly influence the spatio-temporal variability of phytoplankton and hence the Chl-a density in Malacca Strait.

Knowing the accurate Chl-a estimation in marginal seas is essential to understand the global ocean production. Study on spatio-temporal Chl-a variability is foreseen in future research to improve nowcasting of ocean climate change and algal bloom prediction model. This thesis shows the quality assessment procedure on local MODIS Chl-a algorithm for Malacca Straits that accounted impact of spatial variability of low spatial resolution.

The state-of-the-art and accurate local Chl-a algorithm with low impact of spatial variability induced by low spatial resolution in MODIS pixel. The new calibrated Chl-a MODIS could help any future research of marine biology in Malacca Straits (Tan *et al.*, 2006) and to promote the application of MODISA R2013 in marine research. Besides, the MODIS R2013 Chl-a product could support the development of marine database of Malaysia National Oceanographic Data Centre (MyNODC).

Cal/Val exercise needs well-distributed in-situ to increase more match-up sample with satellite observation and this could be carried out by using vessel or by number of scattered bouys to sample Chl-a over the study area. Yet, it becomes more troublesome when the satellite data was hampered by cloud cover or limited number and distribution in-situ points were exist. This could no longer be the issue in this study as the new Chl-a algorithm demonstrates straightforward Cal/Val at promising results with static distribution of in-situ point. The procedure exhibits an alternative way to reduce spatial variability when the option of using the enormous pixel kernel size is needed.

1.6 Study Area

The Malacca Strait has relatively shallower in depth (absolute depth of 300 to 400 meter) than in the South China Sea (60 to 5500 meter depth from the margin to the northeast basin) but both marginal seas contain diverse salinity, temperature and optical water properties due to its geographical features and seasonal climatology. The Malacca Strait is one of the most productive waters in the Malaysia with high nutrient inputs discharged from the rivers (Ali Yousif, 2009) and this in turn intensifies the level of Chl-a abundant. Besides, its coastal water region typically exhibits higher temporal and spatial variations of Chl-a concentration induced from the climatic, biological, physical and chemical condition (Thia-Eng *et al.*, 2000; Abdul Hadi *et al.*, 2013; Haldar *et al.*, 2013). Two in-situ data stations in Malacca Strait measures continuous daily Chl-a located at Payar Island, Kedah (ST1) and Bagan Nakhoda Omar reservoir, BNO, Selangor (ST2). All in-situ Chl-a measurements are provided by Japan International Research Centre for Agriculture Science (JIRCAS) and Penang Fish Research Institute (FRI) for this study. The in-situ Chl-a was measured based on the method proposed by Suzuki & Ishimaru (1990). Figure 1.1 showed the study region with two static in-situ stations and main rivers along the coast of Malacca Strait which are Kerian river (Sg. Kerian), Selangor river (Sg. Selangor), Klang river (Sg. Klang), and Langat river (Sg. Langat) where the river discharge inputs to the Malacca Straits. Malacca Straits has been divided into three sections which are, 1) north, 2) middle and 3) south, because the north and south region are very different in terms of water optical properties, physical oceanography (Andaman Sea water influence northern region and South China Sea water influence southern region), and its bathymetry where north is deep and wide compare to south which is shallow and narrow.

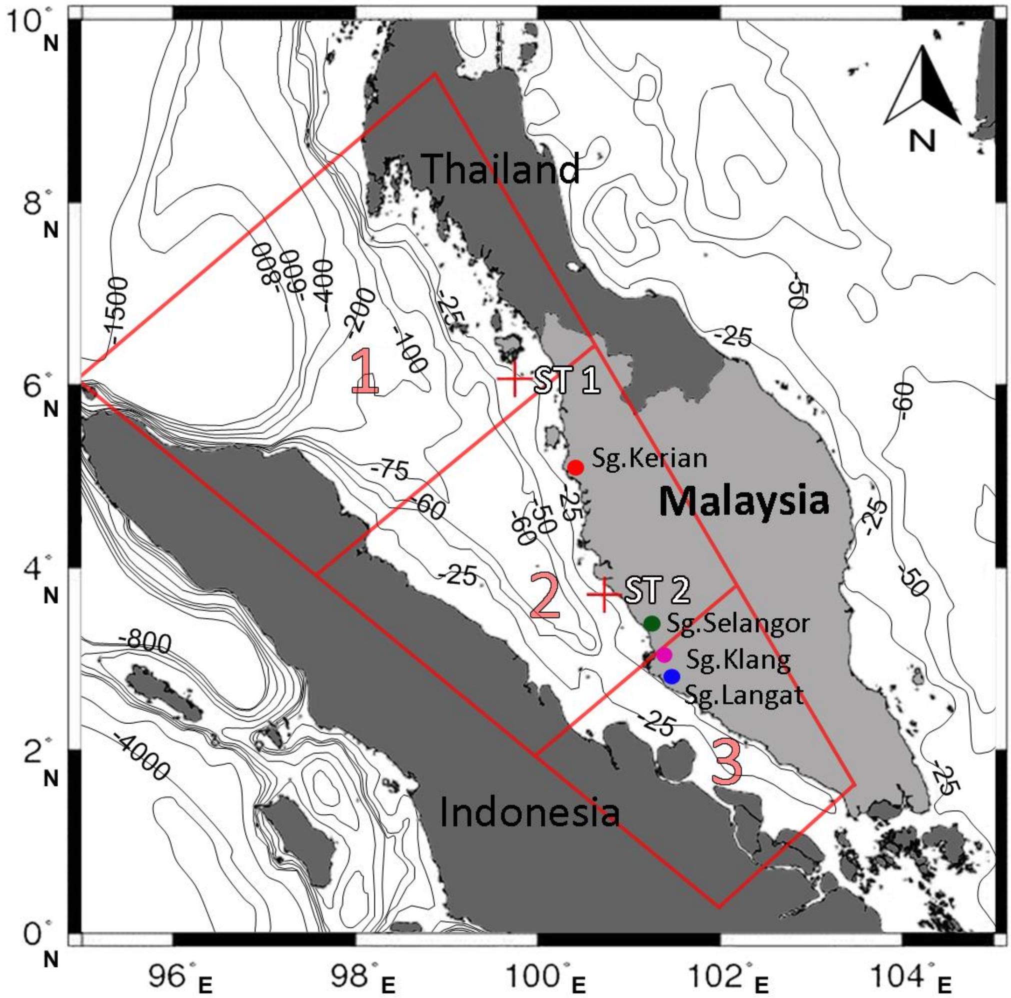

Figure 1.1 Map of Malacca Strait showing two stations, Station 1, ST.1 (northern part) and Station 2, ST.2 (southern part) where the in-situ Chl-a data were taken, three section of Malacca Strait (1-North, 2-Middle, 3-South) and 4 main rivers along the coast of the strait.

1.7 Scope of Study

This study will mainly focus on assessing the spatial variability of the local Chl-a estimation in terms of algorithm statistical analysis, Chl-a estimation bias, and local Chl-a algorithm applied map. The empirical algorithm (OC3M) was used to retrieve the Chl-a and it was calibrated using the in-situ data at two stations in Malacca Strait to achieve the objective of developing the locally-tuned OC3M algorithm using the latest MODISA R2013. The primary data used in this study is the MODISA Level 2 with the resolution of 1km. In this study, the MODISA data was preferred instead of MODIS-Terra because of the 1km and 250m of the MODIS-Terra data has lower SNR and its application mission is not suitable for ocean studies (Xiaoxiong et al, 2005).

To establish the empirical model, the nonlinear regression with reduced major axis (RMA) method is applied. The fitting method presented in this study was implemented for the data sample that met the limitation of the study, which is data sample less than 40 match-up points and the in-situ data was from few static stations that were sparsely distributed. Throughout the Cal/Val process, the standard Chl-a algorithm was locally-tuned in the Case-1 and Case-2 water separately and also in combined water cases. This is to determine the best way that the local-tuned Chl-a algorithm give the best result for the estimated Chl-a value in the study area.

In the accuracy analysis, error of fitting is assessed based on the result of the confidence interval (CI), sum of squares error (SS) and goodness of fit test (gof) and error of data (*i.e.*, induced by spatial variability of MODISA pixel) is evaluated by absolute percentage difference (APD), relative percentage difference (RPD), root mean square error (RMSE), mean normalized bias (MNB) and the correlation of determination R^2. This study sets the APD lower than 35% the positive R^2 as the major argument as the correlation of satellite pixels established with the static in-situ station. Practically, the satellite oceanography processing requires well-distributed in-situ points to increase match-up with synoptic satellite coverage, and this is not the case applied in this study. Correlation to static in-situ introduces spatial variability of MODISA Chl-a, therefore the assessment of this spatial variability impact is carried out by different different sizes of pixel kernels (e.g., 3x3, 5x5 and 7x7) and in turn, optimizing the chances of number of match-ups. To compensate the variability impact, the spatial weight function is employed to the R_{rs} satellite-retrieved and consideration on the temporal window for satellite acquisition to in-situ measurement time is also taken into account.

Malacca Strait is categorize as eutrophic water and in order to test the applicability of the derived locally tuned Chl-a model, the Malacca Strait water was divided into 3 parts (*i.e.*, Northern part which basically is the Case-1 water, Middle part which is basically dual-classification waters and Southern part which is the Case-2 water). Applicability test encompasses estimation of p-value and statistical analysis of the related geophysical parameters (*i.e.*, river discharge, rainfall rate, in-situ SST and suspended sediment) to help in understanding the Chl-a variation during the study period.

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