APPLICATION OF MACHINE LEARNING ALGORITHMS FOR ESTIMATING OCEANIC CHLOROPHYLL-A AND NUTRIENTS

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DEDICATION

To my family and partner,

for their advice, patience, and their faith.

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ABSTRACT

The spectroscopic capability of the satellite observation of ocean colour contributes to the estimation of the concentration of Chlorophyll-a (Chl-a) on the ocean surface. Chl-a can be a proxy in the determination of the phytoplankton biomass distribution, which indicates the trophic status of the water body. Long-term records of ocean colour data at lower spatial resolution of 1 km has been widely used in the derivation of various ocean colour algorithms. Although most of the algorithms perform well in clear water state, the significant uncertainty is evident when algae-prone areas near the coast and shallow water are mapped at the 1-km resolution. Therefore, the current study designed a methodology for new estimation of Chl-a and nutrient concentration in coastal water from multi-platform satellite imageries at medium spatial resolution (10 to 30 m) with systematic accuracy assessment using collocated sea-truth. In particular, Artificial Neural Network (ANN), Support Vector Machine (SVM), and Random Forest (RF) techniques were used to establish the complex relationships of collocated remote sensing reflectance from the consecutive Landsat 8 Operational Land Imager (OLI) and Sentinel 2 MultiSpectral Instrument (MSI) images and in-situ parameters. Using these machine learning methods, this study also demonstrated the estimation of nutrients (nitrate and phosphate). The radiometric resolution of OLI in this study allowed higher overall accuracy of Chl-a estimates in the West Johor Straits (WJS) water. Meanwhile, the ANN recorded higher accuracy of Chl-a and nitrate estimates than that of the SVM and RF variants. Using the ANN, the Chl-a estimates at lower root-mean-square error (RMSE < 6 mg/m^3) and APD of lower than 35% were mapped. The regression between Chl-a and nutrients was remarkably low ($R^2 < 0.2$) on OLI and MSI. However, Fine Tree RF and ANN models improved the precision (RMSE) of nitrate (< 12 μmol/L) and phosphate (< 3 μmol/L). The absence of direct relationships of optical properties and spectral characteristics with nutrients led to higher uncertainties (> 100%), and this made phosphate content estimates in shallow water dubious, resulting in the need for extensive in-situ validation. Machine learning offers powerful estimation capability on Chl-a and nutrient concentration, especially for the higher spatio-temporal variability optical parameter of coastal waters, which was successfully demonstrated in this study through the discussed application in WJS.

ABSTRAK

Kebolehan sepektroskopi satelit pemerhati *ocean colour* menyumbang kepada penganggaran kepekatan klorofil-a (Chl-a) pada permukaan laut. Chl-a adalah proksi dalam penentuan taburan biojisim fitoplankton yang boleh menandakan status *trophic* badan air. Rekod jangka panjang data *ocean colour* daripada sensor *ocean colour* pada resolusi ruang rendah 1 km telah digunakan secara meluas dalam perkembangan algoritma *ocean colour*. Penganggaran kebanyakan algoritma *ocean colour* mencatat prestasi baik dalam keadaan air jernih tetapi ketidakpastian menjadi ketara apabila kawasan dedahan alga berdekatan perairan pantai dan kawasan cetek dipetakan pada resolusi 1-km. Oleh itu, kajian semasa ini merekabentuk metodologi bagi anggaran baru kepekatan Chl-a dan nutrien di kawasan pantai daripada imej pelbagai platform satelit pada resolusi ruang sederhana (10 hingga 30 m) dengan penilaian kejituan sistematik menggunakan data laut terkumpul. Khususnya, teknik rangkaian neural buatan (ANN), mesin vektor sokongan (SVM) dan hutan rawak (RF) digunakan untuk mewujudkan hubungan kompleks antara kumpulan pantulan penderiaan jarak jauh daripada urutan imej *Landsat 8 Operational Land Imager* (OLI) dan *Sentinel 2 MultiSpectral Instrument* (MSI) dan parameter *in-situ.* Melalui kaedah pembelajaran mesin-mesin ini, kajian ini juga menunjukkan anggaran nutrien (nitrat dan fosfat). Resolusi radiometrik OLI membenarkan peningkatan kejituan keseluruhan anggaran Chl-a di perairan Selat Johor Barat (WJS). ANN merekod kejituan anggaran Chl-a yang lebih tinggi daripada varian SVM dan RF. Menggunakan ANN, anggaran Chl-a pada ralat punca min kuasa dua (RMSE < 6 mg/m^3) dan APD kurang daripada 35% telah dipetakan. Regresi antara Chl-a dan nutrien adalah sangat rendah ($R^2 < 0.2$) pada OLI dan MSI. Namun, model *Fine Tree* RF dan ANN telah meningkatkan ketepatan (RMSE) nitrat (<12 μmol/L) dan fosfat (< 3 μmol/L). Ketiadaan hubungan sifat optik terhadap nutrien telah menyebabkan ketidakpastian yang lebih tinggi ($> 100\%$) dan anggaran kepekatan fosfat di perairan cetek diragukan dan sangat memerlukan pengesahan *in-situ* yang menyeluruh. Pembelajaran mesin menawarkan keupayaan anggaran yang kuat terhadap kepekatan Chl-a dan nutrien, terutamanya bagi kevariabelan *spatio-temporal* parameter optik yang lebih tinggi di perairan pantai, seperti mana yang didemonstrasi dalam kajian ini melalui perbincangan kegunaan di WJS.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
APD	-	Mean absolute percentage difference
CDOM	-	Colored dissolved organic matter
Chl-a	-	Chlorophyll-a
CZCS	-	Coastal Zone Colour Scanner
HABs	-	Harmful Algal Blooms
MAE	-	MEAN ABSOLUTE ERROR
MBR	-	Maximum Band Ratio
MERIS	-	Medium Resolution Imaging Spectrometer
MODIS	-	Moderate Resolution Imaging Radiometer
MSI	-	Multispectral Instruments
NASA	-	National Aeronautics and Space Administration
NIR	-	Near infrared
NO3	-	Nitrate
OLI	-	Operational Land Imager
PO4	-	Phosphate
RF	-	Random Forest
RMSE	-	Root mean square error
RPD	-	Relative percentage difference
Rrs	-	Remote Sensing Reflectance
SeaWiFS	-	Sea-Viewing Wide Field-of-View Sensor
SVR	-	Support Vector Regression
TSS	-	Total suspended sediment

LIST OF SYMBOLS

λ	-	Wavelength
nLw	-	Normalized water-leaving radiance
L_w	-	water-leaving radiance
a0 to a4	-	Total coefficient

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Terrestrial activities and ocean processes always receive significant natural resources and inevitable residues from the hectic and intensive anthropogenic activities, resulting in various kind of impacts towards the aquatic ecosystem. These repercussions cause significant impact in the coastal zone (Yasser, 2003). Terrestrial input via nutrient-rich river discharge resulted in high phytoplankton biomass throughout coastal areas, possibly leads to eutrophication algal blooms (Sellner *et al.*, 2003; Wang *et al.*, 2003; Dai *et al.* 2008; Nazmi *et al.* 2013), affects the major economic losses and endangers the human health (Fletcher, 1996; Morand and Merceron, 2005). Estuaries are semi-enclosed coastal area that receive both freshwater and saltwater inflows. They can be classified as vertically mixed, slightly stratified, highly stratified, or saline-wedge (Haron and Tahir, 2015). Several estuaries are also linked to bays that are near to cities and agricultural land (Pour and Hashim, 2016). Rapid urbanization, industrialization and intensifying agricultural production resulting in the increase of nutrient level entering to estuaries, which may lead to water eutrophication eventually (Pour and Hashim, 2016).

Phytoplankton is an essential aquatic photosynthesis organism and plays an imperative role in the oceanic food web that consequently contributes to the world's primary production. Phytoplankton uses photosynthesis pigment such as chlorophyll, and other light-harvesting pigments at the base of the ocean food web to carry out photosynthesis by virtue of the ability to convert sunlight into biochemical energy required for carbon fixation. Large accumulative number of phytoplankton and macroalgal abundant reported in the coastal areas is commonly known as macroalgal blooms phenomenon (Sellner *et al.*, 2003). Blooms commonly live in marine and freshwater environments by eutrophication and limited current flows exploitation (Lim *et al.*, 2005; Pour and Hashim, 2016). Several international efforts have taken serious reduction measures on number of algal blooms cases by studying the the spatio-temporal trend and introducing some new policies to contain them. In many European countries, algal blooms cases have been reduced through effective monitoring under the UE legislation since 1991 (UNESCO, 2016). In Malaysia, Sabah has been known as the hotspot for the harmful algal blooms (HABs) and the red tide outbreaks. Consistent monitoring of algal blooms by the Department of Fisheries Sabah since 1976 keeps the safety of seafood for the local food consumption (Jipanin *et al.*, 2019).

Chlorophyll-a (Chl-a) measured in mg/m^3 significantly contributes to the primary productivity in ocean livelihood ecosystem (Feret *et al.*, 2018) by the formidable relation with many important biophysical and biochemical parameterization such as nutrients and salinity (Gitelson *et al.*, 2014; Houborg *et al.*, 2015). Accurate measurement of Chl-a along with corresponding oceanic nutrients is vital in successful phytoplankton monitoring where various oceanic parameters as inputs to the marine agricultural system in complex water conditions for productivity estimation are involved (Giardino *et al.*, 2019). Existing in situ Chl-a and nutrient observation applies complex procedures to sample the algae bloom attributes (Zeng and Li, 2015). The design of sampling routine either in once, twice or more per month is dependent on the reporting area at risk of red tides and Paralytic Shellfish Poisoning (PSP). Water samples taken from the site instrumentation to the lab analysis provides information about the chlorophyll contents and cell abundances estimation (Sellner *et al.*, 2003). Yet, the process is tedious, labor-intensive work, time-consuming, costly and, in fact, less practical particularly for such large area where high number of samples are needed. In recent years, remote sensing has received a lot of attention in Chl-a and nutrients mapping. Narrowband hyperspectral and multispectral sensing capabilities offer reliable, quick, cost-effective and even more practical method for synoptic mapping routine.

Unlike conventional in-situ sampling, satellite remote sensing becomes a practical apparatus to monitor the marine environment at better spatio-temporal observation in which the spectroscopic and synoptic capability allows quantification on the biophysical impact of eutrophication at higher spatial and temporal accuracy

(Holt *et al.*, 2017). Satellite remote sensing missions have served for the last 30 years to provide spatially and temporally comprehensive raster data of the photosynthesis pigment and the Chl-a which strongly manifesting the algae bloom presence. This ocean color information can be used to estimate the concentration of other substances in the ocean by measuring variations in the spectral quality of the water surface (IOCGG, 2000).

Satellite ocean color gives synoptic information about the spectral water-leaving reflectance, which is eventually can be used to quantitatively decompose the marine inherent optical properties (IOPs) and the apparent optical properties (AOPs) by means of the correlation with the Chl-a concentration, DOM, and particulates material (Werdell *et al.*, 2018). The water leaving radiance measured in the visible portion of electromagnetic radiation quantifies the presence of these substances in the ocean surface waters. The visible spectrum is selectively being absorbed by specific Chl-a pigments indicating the presence of phytoplankton. In 1978, NASA launched the Coastal Zone Color Scanner (CZCS) on Nimbus-7 with the ability of detection and measuring the Chl-a concentration in the ocean skin. The CZCS mission was terminated in June 1986 after stability problems causing large uncertainties in the radiometric calibration (Evans and Gordon, 1994). Some series of ocean colour mission were initiated for daily operational routine with an improved instrument specification and capabilities such as OCTS (1996-1997), SeaWIFS (1997-2010) and MERIS (2002-2012) (O'Rilley and Werdel, 2019). The most prominent ocean colour sensors by NASA are SeaWIFS and the following MODIS in 2002 providing continuous observation for global coverage data across the visible spectrum and narrowly defined band at minimum noise level (Robinson, 2004).

The CZCS mission has proved the advancement of Chl-a estimation by ocean color sensing in the early 1980s. The most successful algorithm for estimating Chl-a concentration is band ratio, depicting the ratio of the blue reflectance to the green reflectance known as the blue-green ratio (O'Rilley and Werdel, 2019). The application of blue-green ratio requires reflectance of at least one narrow blue band and one green band despite of the fact that more spectral bands are applied for study in coastal and shelf waters. As the ratio of blue to green gets lower, the water appears greener, hence increased the Chl-a estimation. It is known that underwater optics or inherent optical properties (IOP) are related to the concentration of chlorophyll, DOM and particulates materials (Robinson, 2004). However, there was no method to derive purely from the underwater optics and thus determines the concentration of water parameters. The most reliable approach is by using empirical algorithm on the measured reflectance data. The empirical algorithm involves the sea-truth Chl-a and radiometric observation of the normalized water-leaving radiance (*nLw*) or the remote sensing reflectance (*Rrs*) at several wavelengths. Nevertheless, the empirical algorithm requires higher correlation between both inputs but the regression may become more complicated when the water condition is getting complex and heterogenous.

Morel and Prieur (1977) have divided the marine water into two categories; Case-1 or Case-2 water. Special ocean colour retrieval algorithm has been designed either for retrieving the bio-optical model from both types of waters. Case-1 water has water optical properties that are dominated by phytoplankton and co-varying in-water constituents, whereas the Case-2 water has water optical properties that are influenced more by other in-water constituents in the form of organic or inorganic particles and vary without phytoplankton. The empirical algorithm likely encounters the inherent bias associated to Chl-a estimation when applying on the Case-1 and Case-2 water simultaneously. This complex water condition embarks eutrophication, which is defined as the response of aquatic ecosystems to nutrient loading (Edmondson, 1991).

Innovative effort in combining the standard band ratio algorithm with the colour index (CI) method was initiated by the studies of O'Rilley *et al.* (1998) and Hu *et al.* (2012) to produce generalization in the Chl-a estimates for all ocean colour missions (O'Rilley and Werdel, 2019). Yet, the improved algorithm is only applicable to clear water (i.e. Case-1 and open ocean). There were initiatives to retrieve Chl-a in the coastal region using band-ratio variants but it was difficult due to the optically influence of other in-water substances (regardless of Chl-a presence) that resulted in underestimation of satellite derived Chl-a (Yang *et al.*, 2018). Previously, the green or near-infrared (NIR) bands were frequently used in conjunction with the red band. In shallow coastal water, bottom reflectance has a strong influence on the green band with low attenuation effects. Several studies also have applied the red band in Chl-a algorithm development for shallow coastal water. The red band can work at certain surface water depth by hypotactically assuming that the spectral energy has high attenuation capability and less effects by the bottom reflectance and the colored dissolved organic matter (CDOM) spectral residue. An algorithm based on the backscattering coefficients at NIR bands to determine the Chl-a concentration was also introduced to demonstrate the red-NIR algorithm applicability especially in the estuarine water (Abbas *et al.*, 2019). Besides, previous Chl-a studies were experienced overestimation by the inevitable spatial bias and this was particularly evident for the MODIS derived Chl-a at 1-km resolution even by the finer band spectral resolution at 443, 490 and 560 nm.

In Peninsular Malaysia, MODIS data have been utilized in mapping the Chl-a concentration. The data was limited to open ocean and less suitable for coastal mapping due to low spatial resolution. Study by Lah *et al.* (2014) reported that the MODIS OC3M algorithm endured overestimation in the Case-2 water of Malacca Straits. Despite of fairly acceptable Chl-a estimation with the absolute percentage difference (APD) of less than 35% was reported for Case-1 water, there was higher APD (>90%) at measurement near to the coast due to Case 2 optical water effect. The study found that the Chl-a homogenous distribution designated for low spatial resolution data was violated by the Case 2 water causing extensive overestimation in which the Chl-a was sparsely distributed in heterogeneous fashion within the 1-km spatial extent. During the orbit cycle, MODIS exhibit larger day-to-day variability in percentage difference for most of the coastal conditions. The relatively lower energy signal in the red channel embarked the highest APD (up to 25%) amidst all other channels. The red channel (*Rrs* 655) encountered the largest discrepancies in coastal waters whereas blue channel (*Rrs* 443) is found to be the most dependable product for oceanic surface with Chl-a < 0.3 mg/m3 (Pahlevan *et al.*, 2016; Moore *et al.,* 2015). Even though, previous studies highlighted high productivity of coastal water, the accuracy of Chl-a has been compromised by low sensor spatial resolution and environmental factors such as cloud cover (>40%).

The limiting nutrients for algal biomass are frequently recognized as nitrogen and phosphorus, whereas silicon is required for diatom growth (Hecky and Kilham, 1988). Nitrogen can be found in a variety of forms, including dissolved nitrogen, amino acids, amines, urea, ammonium (NH4+), nitrite (NO2-), and nitrate (NO3) (NO3-), in fresh water (Limnology, 2001). In aquatic ecosystems, phosphorus (P) can be found either in particulate matter or as soluble inorganic phosphorus, orthophosphate (PO43-) (Knud-Hansen, 2017). The increasing eutrophication in receiving water bodies were connected to nutrient inputs from contributing watersheds and rivers (Pinckney, *et al.*, 2001; Smith, 2003; Abbas *et al.*, 2019). Significant progress has been achieved in understanding the dynamics of natural and anthropogenic nitrate and phosphate inputs to coastal waters over the last few decades. The recognition of human impact on the nitrate and phosphate cycles has sparked a lot of research into how to better manage these nutrients. Anthropogenic nitrate and phosphate production from contributory agriculture, industrial, and human activities have significantly increased the amount of N and P in water bodies, resulted to the widespread eutrophication of both inland and coastal waters (Pinckney *et al.*, 2001; Smith, 2003; Abbas *et al.*, 2019). Study in Šibenik Bay area observed the strong influence of the freshwater inflow of the Krka River station, where maximum values of nitrate (57.93 μmol/L) were recorded (Bužančić *et al*., 2016). According to Goi (2020), data in 2016 and 2017 has shown that most of Malaysia's river water quality was in Water Quality Index Class II and Class III. The status of marine water quality in Malaysia shows the threshold of the nitrate and phosphate level, 60 mg/L and 75mg/L for Class II and Class E (mangroves, estuarine and river-mouth water) and 700 mg/L and 670 mg/L for Class III (ports, oil and gas fields) (Department of Environment, 2009).

Commonly, the patterns and trends in nutrient concentrations is based on traditional monitoring approaches, such discrete and nonsynchronous samples collected manually at weekly to monthly intervals followed by days to weeks for laboratory analyses to be completed. While this low temporal frequency approach — coupled with modeling and statistical techniques has yielded critical information. However, more significant manpower and cost were involved. This is particularly important for episodic events such as floods that are difficult to anticipate but can have significant and long-term ecological, economic, and human health effects. Remote sensing has provided a tool for monitoring changes in coastal waters (Choi *et al*., 2012;

He *et al*., 2013; Markogianni *et al*., 2018). Higher spatial and temporal resolution, in particular, made it easier to observe highly dynamic and small-scale changes in coastal waters (Choi *et al*., 2012; He *et al*., 2013; Markogianni *et al*., 2018). However, most studies on water quality remote sensing have mainly focused on optically active variables (He *et al*., 2008). Some water quality parameters, such as nitrate and phosphate concentrations, have no direct optical properties and spectral characteristics and cannot be directly observed by current satellites (Mobley, 1994; Gholizadeh *et al.*, 2016; Dong *et al.*, 2020). Yet, these nutrients can have a strong correlation with optically active variables that can be estimated by remote sensing (Kutser *et al*., 1995; Chang *et al*., 2015).

It is very challenging to obtain high correlation between spectral data and in-situ measurement. The accuracy of Chl-a and nutrients has been hampered by environmental conditions and low sensor spatial resolution. Landsat 8 OLI and Sentinel 2 MSI has relatively fine spatial resolution in the ocean color perspective, with 30 and 10 m resolution respectively, and this has embarked a remarkable coastal mapping capability. OLI provide medium-resolution sensors with push broom sensor and 16 bits DN, which allows for significantly higher signal-to-noise ratio (SNR) to monitor biophysical changes and improved OLI pigment discrimination ability more precisely in the coastal water (Pahlevan *et al.*, 2014). MSI, with two twin satellites (Sentinel-2A and Sentinel-2B), with a high 12-bit radiometric resolution generates spectral images with 13 bands in varying wavelength (433 nm to 2190 nm), respectively. Unlike MODIS, MSI and OLI spatial resolutions are better in resolving spatial information of surface Chl-a in the region near to shore. Additionally, MSI provides scenes in 290 km swath and a revisit time of five days at the equator to the OLI which operates on a 16-day cycle (USGS, 2016). The new coastal/aerosol band, centred at 443 nm OLI, enables for the determination of the upper water column's inherent optical properties (IOPs) near the Chl-a peak absorption. Furthermore, the MSI may be qualified to a wider variety of Chl-a retrieval techniques than the Landsat 8 OLI due to the presence of a red-edge band centred near the 705 nm wavelength in the near infrared (NIR) (Beck *et al.*, 2016).

By recognizing the nonlinearity and impact of complex optical interaction over the eutrophic water, this research motivated to designs a methodology for Chl-a and nutrient content from multi-platform satellite imageries using machine learning techniques over West Johor Straits. The advancement of machine learning techniques, with moderate satellite sensor, OLI and MSI has embarked a remarkable coastal mapping capability and resolve the complex relationship over the study area (Ouma *et al.*, 2020). The machine learning allows complicated water types to be correlated to the inherent optical properties (IOP), apparent optical properties (AOP) and the measured Chl-a in-situ (Ioannou,2011). Through this algorithm, the best machine learning was assessed to reduce the spatial and temporal variabilities impact on satellite data compared to existing ocean color algorithms. The results provide information on monitoring trophic status along the coastal water and to assess the future challenges in this unique water condition.

1.2 Problem Statements

Spatial attributes of Chl-a derived from satellite ocean colour vary significantly in the coarse resolution imagery and at limited visible bands. Despite the introduction of modern and precise sensors, large margin of uncertainty in the satellite estimation of Chl-a concentration in coastal waters is apparent by the bottom reflectance in shallow water systems (Abbas *et al.*, 2019). Unlike the single spectral band ocean colour algorithm, the band ratio algorithm reduces the unwanted scattering energy as well as the inherent atmospheric attenuation. The algorithm is widely used but limited for open ocean and Case 1 water type. Although the band ratio has been demonstrated to surpass semi-analytical algorithms in determining Chl-a in oceanic and coastal waters (Brewin *et al.*, 2015), the accuracy of Chl-a derived was poor for coastal waters (Zheng and DiGiacomo, 2017). According to Tilstone *et al.* (2021), the accuracy of satellite derived Chl-a concentration should meet the APD below 35% in the quality standard of NASA. In Case 1 water, the standard ocean color algorithm can derive acceptable accuracy of Chl-a content (APD<35%). However, in Case 2 water where the correlation among visible bands becomes weaker, the APD may exceed 35%. Thus, the research in band ratio focuses on the assessment of Chl-a estimation in Case 2 water. The combination of multi-band ratio has been identified to complement such limitation by single band ratio. As far as literature was concerned, no analysis has ever been conducted to determine the best band ratio combination for estimating the Chl-a particularly in the complex water condition. This study exploits the potential of multi-band in visible spectra which is available in the modern remote sensing satellite.

The resolution of current ocean color sensors remains one of the most constraining factors for Chl-a retrieval in nearshore areas, as they are unable to resolve coastal ocean characteristics accurately (Mouw *et al.*, 2015). The Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Aqua satellite launched in 2002 with data at 36 spectral bands is extensively used to measure the Chl-a concentration worldwide (Gierach *et al.*, 2017; Poddar *et al.*, 2019). In optically complex water, the coarse spatial resolution (1 km at nadir) and uncertainties associated with equipment calibration and data processing methods limit the ability to monitor the Chl-a concentration (Trinh *et al.*, 2017). Over optically complicated waters, Moore *et al.* (2015) reported the bias levels for Aqua MODIS is APD>35% (Zibordi *et al.*, 2015). Albeit the filtered standard deviation divided by the filtered mean threshold (CV) was introduced in MODIS studies to eliminate simulated outliers, the daily simulated percent difference (PDs) can reach as high as ±18% (Pahlevan *et al.*, 2016). The largest PDs may be accounted to algal bloom events and terrestrial inputs influxes. The commission of Operational Land Imager (OLI) on board the Landsat 8 and Multispectral Instrument (MSI) on-board Sentinel-2 offering ocean colour bands at 30 m and 10 m resolution respectively, could contribute to the spatial and accuracy enhancement in the Chl-a retrieval over coastal waters region (Lobo *et al.*, 2015; Watanabe *et al.*, 2017).

Number of good qualities MSI images is significantly higher than that of OLI throughout the year. MSI provides images at three times more than of the OLI throughout the year due to the dual revisiting time advantage. There is significant overestimation in OLI radiometric accuracy, but modest underestimation can be observed for MSI. The difference in radiometric resolution between both sensors (i.e., 16 bits at maximum 65536 DNs for OLI and 12 bits of 4096 DNs for MSI) has induced signal saturation. This saturation may be more noticeable on bright and intensely reflecting surfaces, and it may be amplified by the difference in field of view (FOV) (Dagar *et al.*, 2019). Such issue regulates the relation between optical properties and Chl-a to be even more complex and this study foresees the artificial intelligence with complex modeling capability is apparently the possible solution. Utilization of the artificial intelligence on OLI and MSI is novel, and indeed no study using OLI and MSI to estimate the Chl-a was reported in coastal region of Peninsular Malaysia especially at West Johor Straits.

Nitrogen (*N*) and phosphorus (*P*) are vital nutritional elements for primary production. In coastal region, nutrients are usually conservative (Wang *et al.*, 2018). Many studies have shown the capability of satellite remote sensing to monitor the spatiotemporal variability of these nutrients (Trinh *et al.*, 2017). Oceanic nutrient mapping remains difficult because some nitrate and phosphate concentrations, are hardly detected by the existing satellites. Dissolved nitrogen and phosphorus have no significant spectral response and not optically active in the visible and near-infrared spectrum (Gholizadeh *et al.*, 2016; Dong *et al.*, 2020). Some empirical models have been established based on nutrient relationships with Chl-a, and other optically sensitive materials (Huang *et al.*, 2015; Huang *et al.*, 2016). Though such relationship is usually unstable and less accurate due to other factors such as large river run-off and salinity influence. The basis of this issue is the complex relation was established between nutrients and optical properties with spatio-temporal variability by the water condition. Thus, machine learning regression could offer a way to accurately develop this complex relation at the expense of the spatio-temporal variability of the water condition.

1.3 Research Questions

The research question is expected to be the important indicator that will highlight the main idea for this research.

(a) How the new combination of band ratio improves the current ocean color model?

(b) How to develop machine learning model from OLI and MSI data to estimation of Chl-a and nutrients concentrations?

(c) What are the accuracy and the limitation of the machine learning in the Chl-a and nutrients estimation?

1.4 Research Aim and Objectives

This research aims to designs a methodology for Chl-a and nutrient concentration estimation from multi-platform satellite imageries using machine learning techniques over West Johor Straits and the accuracy assessment of Chl-a estimates using on-site measurements. The objectives of the research are:

(a) To determine the best band ratio combination from different optical bands of OLI and MSI for Chl-a estimation

(b) To develop machine learning model to estimate the Chl-a and nutrient concentration from multi-band ratio combination between optical satellite and in-situ measurement

(c) To assess the accuracy of satellite derived Chl-a and nutrient concentration

1.5 Scope of the Study

This study mainly focus on designs a methodology for Chl-a and nutrient estimation from multi-platform satellite using machine learning techniques. The primary data used in this study is sea truth measurement and remote sensing data. Among platforms that provide open access to imagery, the Landsat 8 OLI (Operational Land Imager) (Concha and Schott, 2014; Boucher et al., 2018) and multi-spectral imager (MSI) on board the ESA's Sentinel 2 platform (ESA-European Space Agency, 2015) with medium-spatial resolutions at 30 and 10 meters, respectively, seems to offer the best combination of spatial, temporal and spectral coverage for Chl-a retrievals in coast and inland waters. The improved radiometric resolution of Landsat-8/OLI with reduced image noise and spectral heterogeneity is observed to be particularly significant in precise water surface extraction and water quality retrieval

(Nguyen et al., 2016). For MSI, aside from its high temporal resolution (five days) and 12-bit radiometric resolution, the sensor also delivers high radiometric dynamics for the observed water surfaces, promoting more precise Chl-a mapping in recent times (Watanabe et al., 2017). Images from these sensors were selected with cloud covers (below than 10% octave level).

The atmospheric correction algorithm applied for OLI and MSI image, using C2RCC processor from SNAP. This data was selected to analyse the Chl-a and nutrients estimation in West Johor Straits from 2017 to 2018 to match with sea truth measurement. Synchronized in situ measurement and satellite data were used with the allowance of ±7 days of differences. The time window may increase without introducing significant uncertainty into the model (Kayastha *et al.*, 2022). For OLI, 48 matches were found, while 103 for MSI. Four sampling points were chosen in West Johor Straits. Pixel averaging were applied on available image using 3x3 window kernel at each of sampling station, to optimize the chances of number of match-ups.

Coincident sea truth measurements were collected gives information on the Chl-a, and nutrients and used for the Chl-a and nutrient modelling, up to twice a month from 2017 to 2018. The sampling station provided Chl-a, sea surface temperature and nutrients data from four sampling stations. Rainfall data was obtained from Malaysian Meteorological Department (2020), Malaysia. West Johor Straits is active with aquaculture and received influence from rivers nearby and categorized as eutrophic water. This area were chosen because they were involved in bloom events reported by Lim *et al.* (2012) and Fisheries Research Institutes Penang (2017).

This study only focused on Chl-a and nutrient estimation, at four sampling station in West Johor Straits. The best band ratio combination and single band were defined to select the best input for Chl-a and nutrient modelling using three different approach machine learning, artificial neural network, support vector regression and random forest model in MATLAB. The optical data from OLI and MSI were used to estimate the Chl-a and nutrients model through the non-linear least square optimization by the Levenberg-Marquart (LM) method, two kernel support vector regression (Linear and Gaussian) and regression tree (Fine Tree, Medium Tree and Coarse Tree) by 5-fold cross validation. These methods were applied to determine the best model and to solve the non-linear relation between the optical data and nutrients.

1.6 Significance of the Study

The monitoring of water quality parameters has become a major challenge because of effort-intensive, time consuming and unsuitable for large area. This study presents a novel and local machine learning model to estimate Chl-a concentration for WJS from remote sensing measurements. The marine authority would benefit from this study, as well as FRI and Department of Fishery, Chl-a estimate is relative to the phytoplankton and higher resolution Chl-a map from OLI and MSI at 10 to 30-meter scale and 10-day observation attributed the spatial and temporal distribution of algal bloom. Coincident shoreline changes compliments to the Chl-a resulting in the comprehensive interpretation of the impact of anthropogenic and geographical variations along the shoreline. The results are reliable in mitigation strategy and management of Chl-a impact towards sustainable ocean productivities, maritime communities, and climate in Johor water territory. Not to mention, the remote sensing images are freely accessible online and available for long period archive.

Chl-a estimation by band-ratio algorithms always experiences complicated extraction and overestimation particularly over the ocean with Case-2 water type. The band-ratio algorithm usually applies a ratio of blue to green reflectance and exhibits higher Chl-a due to the lower green reflectance. This study introduces the machine learning model that is trained by the actual and accurate Chl-a measured at the scene and contains complex relations between Case-2 waters. Results of the machine learning show robust and highly accurate Chl-a estimates regardless of the water type at the pixel position. The machine learning model allows a user to apply all reflectance data in all bands and the band-ratio combination and finding the best combination for the models. Thus, it helps scientist and The Intergovernmental Oceanographic Commission of UNESCO (IOC) to focus only on the image interpretation of derived Chl-a map and rapidly understand the process for Chl-a spatial and temporal distribution.

1.7 Research Outline

This thesis is divided into five chapters. Chapter 2 reviews past studies to identify the state of the art of Chl-a, ocean colour remote sensing, and to assess the past and present sensor of ocean color satellite, application of machine learning in water quality parameter estimation and coastal geomorphology impact on the Chl-a and nutrients variability, and to identify the research gaps from those studies. In estimating Chl-a and nutrients, the best band ratio and best band combination were determine for machine learning model development. This study depicts the pre-processing and processing schemes by specifying the criteria of the input, output and statistical assessments at every processing stage. Both ocean color band ratio and machine learning approach for deriving Chl-a and nutrients from OLI and MSI were performed in this study for the West Johor Straits. These details on the methodology are described in Chapter 3. The results, analysis and discussion are assembled in Chapter 4, while Chapter 5 comprises the conclusion, contribution to knowledge and recommendations of the study. The fundamental of ocean remote sensing is included as an Appendix A, in which the optical ocean remote sensing were explained.

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LIST OF PUBLICATIONS

Non-indexed Journal

1. Ridzuan F. N. S., Reba M. N. M, Mohd Din M., Hashim M., Lim P. T., Ibrahim Z. and Abdul-Wahab M. F. (2020) Spatial variability assessment on the high resolution Chlorophyll-A extraction from Landsat 8 imageries in Johor waters. *Special Issue of Journal of Engineering Technology and Applied Physics (JETAP)*, 1, pp. 38-43.

2. Fatin Nabihah Syahira Ridzuan, Ami Hassan Md Din, Nornajihah Mohammad Yazid, Muhammad Faiz Pa'suya and Nadia Hartini Mohd Adzmi (2020) Evaluation of Geoid Model in Johor Region Using Global Geopotential Models and GPS Levelling Data. International Surveying Research Journal, 7, pp. 19-36.

Non-indexed Conference Proceedings

1. Ridzuan F. N. S., Reba M. N. M, Mohd Din M., Hashim M., Lim P. T., Ibrahim Z. and Abdul-Wahab M. F. (2019) Spatial variability assessment on the high-resolution Chlorophyll-A extraction from Landsat 8 and Sentinel 2 imageries in Johor waters. *IEEE Workshop on Geoscience and Remote Sensing 2019 (IWGRS2019)*.

2. Ridzuan F. N. S., Reba M. N. M, Mohd Din M., Hashim M., Lim P. T., Ibrahim Z. and Abdul-Wahab M. F. (2019) Shoreline delineation using the long-term Landsat mission for defining the coastal morphology changes from 1980s to recent in Pantai Sabak, Kelantan. *International Graduate Conference of Built Environment and Surveying (GBES) 2019 Proceedings,* 1, pp. 453-459.

3. Ridzuan F. N. S., Reba M. N. M, Mohd Din M., Hashim M., Lim P. T., Ibrahim Z. and Abdul-Wahab M. F. (2020) Estimation of Chlorophyll-A Estimation using Band Ratio and Machine Learning Technique in Johor Waters. *15th Pan Ocean Remote Sensing Conference Proceedings*, Vol.1, pp. 38-42.

Book Chapter

1. Nuhu, S.K., Reba, M.N.M., Abd Manan, Z., Alwi, S.R.W. and Ridzuan, F.N.S. (2022) Assessing the Criteria of Eco-Industrial Park Site Selection for the Sustainable Development Goals Initiatives. In *Sustainability Management Strategies and Impact in Developing Countries*. Emerald Publishing Limited.