International Journal of the Physical Sciences Vol. 5(10), pp. 1489-1495, 4 September, 2010
Available online at http://www.academicjournals.org/IJPS
ISSN 1992 -1950 ©2010 Academic Journals

Full Length Research Paper

MODIS satellite data for modeling chlorophyll-a concentrations in Malaysian coastal waters

Maged Marghany* and Mazlan Hashim

Institute of Geospatial Science and Technology (INSTEG), Universiti Teknologi Malaysia 81310 UTM, Skudai, JohoreBahru, Malaysia.

Accepted 12 August, 2010

This study is compared among four algorithms for mapping chlorophyll-a spatial variations from MODIS satellite data along the east coast of Malaysia. These algorithms are: (i) Aiken's, (ii) Clark-3-bands, (iii) Gordon and (iv) Normalized Difference Chlorophyll Index (NDCI) algorithm. The results show that the Aiken's algorithm is appropriate for accurately synoptic chlorophyll mapping distribution. In fact, the algorithm performs the lowest root mean square error of ±0.10 mg/m^3 as compared to other algorithms. In conclusion, MODIS data can be used as a computing tool for accurately mapping chlorophyll concentration along the coastal water of Malaysia with the implementation of Aiken's algorithm.

Key words: MODIS satellite data, chlorophyll, Aiken's algorithm, Clark-3-band algorithm, Gordon algorithm.

INTRODUCTION

Accurate chlorophyll data are critical for determining the magnitude and variability of global ocean primary production, the effect of biological processes on carbon dioxide drawdown in surface waters and for improving our understanding of phytoplankton dynamics in the oceans. In fact, the phytoplankton is the marine biological key parameter that described the amount of chlorophyll-a concentration. Further, the highest concentrations of phytoplankton are found on continental shores as compared to offshores. This could contribute to the abundance of nutrients that are coming from the land. In this context, the concentration of chlorophyll-a (hereafter chlorophyll), the dominant photosynthesis pigment in phytoplankton, is widely used as a proxy for phytoplankton abundance and biomass. Fortunately, the application of remote-sensing technology from space is providing biologists with means of acquiring these synoptic data sets.

The major task of biological oceanographers is documentation of temporal and spatial variations in the distribution and abundance of marine organisms over a wide scale. In this context, the major challenge is that most of the conventional marine surveying techniques are not able to cover a wide region of the ocean in the earth's surface. Quite clearly, to understand ocean productivity, biological oceanographers must be able to conduct simultaneous measurements over broad areas of waters (Pattiaratchi et al., 1994; O'Reilly et al., 1998; Montres-Hugo et al., 2008). This requires the collection of asset of reliable synoptic data that specify variations of critical environmental parameters and of the abundance and distribution of phytoplankton over a wide region for discrete moments (Pattiaratchi et al., 1994).

Consequently, optical remote sensing techniques over three decades have shown a great promise for mapping chlorophyll-a variation over oceans (Aiken et al., 1994). For instance, coastal zone color scanner (CZCS) on Nimbus, SeaWiFS and MODIS satellite data provide valuable information about chlorophyll-a concentration. In this context, several algorithms have been established to model chlorophyll-a concentration. These algorithms are based on the nonlinear relationship between electromagnetic spectra of the blue and green portions with *in situ* measurements of chlorophyll-a concentrations. Consequently, scientists used for instance, hyperbolic mathematical algorithm or a combination of power with hyperbolic mathematical algorithm to estimate chlorophyll-a concentration. These algorithms usually use the ratios of reflectance in blue and green bands or combinations of ratios as parameters

*Corresponding author. E-mail:magedupm@hotmail.com.

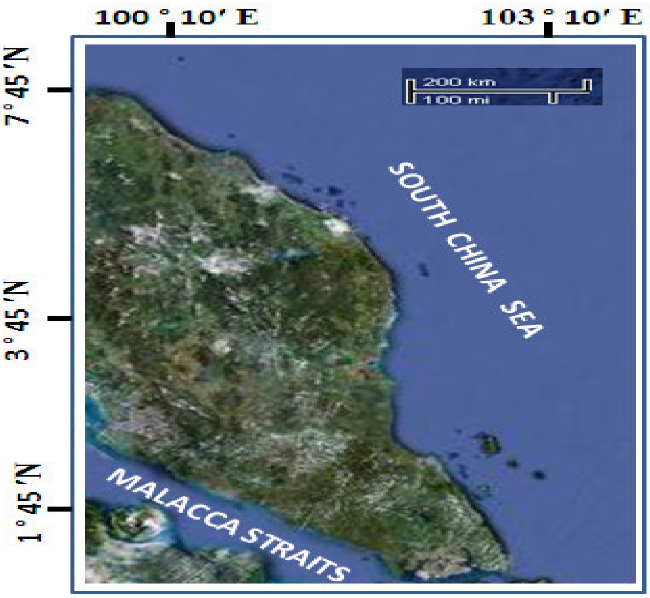

Figure 1. Location of the study area.

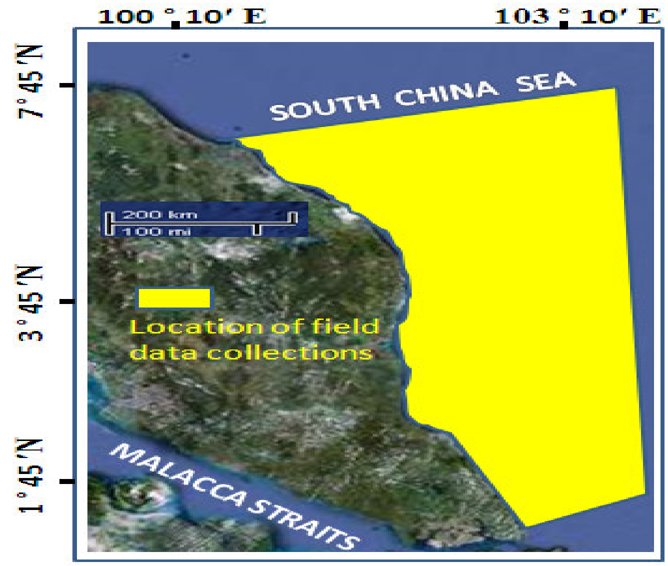

Figure 2. Location of field data collections.

(Montres-Hugo et al., 2008). In doing so, these algorithms involve a nonlinear statistical regression. Therefore, chlorophyll-a is estimated as a function of reflectance ratios, in which nonlinear methods are used for developing transfer functions (Pattiaratchi et al., 1994). In practice, application of the algorithm without preliminary calibration may work accurately, but on the other hand, it may lead to a large deviation from the real values of chlorophyll-a. This study, therefore, has hypothesized that not all nonlinear algorithms show an excellent promise to estimate a chlorophyll-a concentration in such tropical area as Malaysia. In this manner, this study aims to determine an appropriate algorithm which can be used accurately to estimate chlorophyll-a concentrations. In doing so, a comparison between Aiken's, Clark, Gordon and NDCI algorithms is carried out using linear regression statistical model to find out accurately, the algorithm for Malaysian coastal water in determining the concentration of chlorophyll-a.

RESEARCH METHODS

Study area

The study area is situated along the east coast of peninsular Malaysia between latitude 1° 45′ N to 7° 45′ N and longitude 100° 10′ E to 103° 10′ E (Figure 1). In this context, the east coast of Malaysia is dominated by wind monsoon impacts. The monsoon winds play a great role to divide the Malaysian climate into: (i) south west monsoon, (ii) inter-monsoon, (iii) northeast monsoon and (iv) inter-monsoon between northeast and southwest monsoon seasons (Maged, 2009a, 2009b, 2009c). The maximum wind speed of 10 m/s can be found during northeast monsoon period which starts from the month of November to March (Maged, 2001, 2003; Maged et al., 2002; Maged and Mazlan, 2009). Furthermore, Maged (2010) stated that the east coast of peninsular Malaysia borders the South China Sea (the largest water body in Southeast Asia) and faces the continental shelf of Sunda platform, which has water depths not exceeding 100 m.

Field data collections

The study is conducted between 2002 and 2007 along the east coast of peninsular Malaysia. The first phase is carried out in September 2002 along the coastal waters of Kuala Terengganu whereas the second phase is carried out in October 2003 in Phang coastal waters, Malaysia (Figure 2). Further, the oceanography cruises are conducted on Phang coastal waters during September 2003 and April 2004. In addition, *in situ* measurements are acquired in Johor coastal waters in October 2004 and January 2005. Finally, resampling in the coastal waters of Terengganu was carried out in April to June 2007 to ensure accurately *in situ* measurements. In doing so, 105 sampling locations are chosen to study the coastal oceanography of the South China Sea (Figure 2). Chlorophyll samples were obtained from triplicates of vertical haul chosen at different transects by using the 122 microns and 0.6 m of mouth diameter Kilahara net during the day. Samples were fixed with 5% formaldehyde and buffered with borax. Further, the number of spectral measurements was at least 3 on each occasion for each of the 35 field visits from September 2002 until April 2007. An average of the reflectance measurement was fed into the regression equation.

The profiling reflectance radiometer (spectroradiometer) has three of the MODIS wavelength bands namely: bands 9 (438 - 338 nm), 11 (526 - 536 nm) and 12 (546 - 556 nm). Following the procedures done by Montres-Huge et al. (2008), the underwater sensor was deployed just below the water surface, while the downwelling irradiance and upwelling radiance were recorded. In fact, the spectral differences of upwelling light (water-leaving radiance) from a water body are primarily due to light scattered in the backward direction off the particles and molecules of seawater. This is the only portion of the total observed radiance which contains quantitative information, concerning the concentration of ocean constituents, which are measurable by remote sensing sensors from many platforms (Ayman et al., 2007). According to

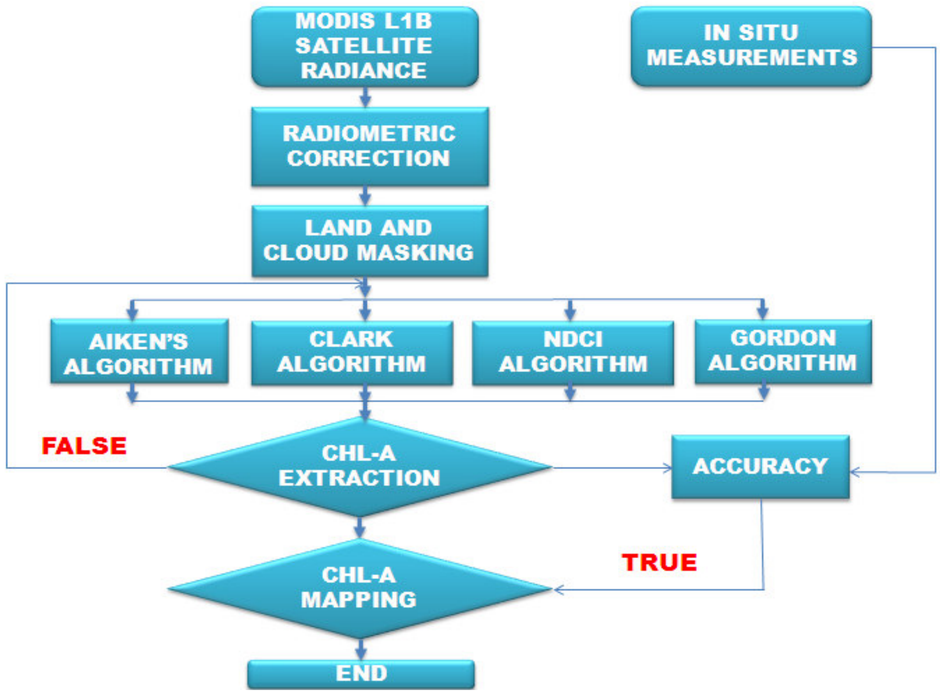

Figure 3. Flow chart for Chl-a modeling from MODIS satellite data.

Table 1. Empirical algorithms (Maged and Mazlan, 2010).

Algorithm	Type	Equations	Band ratio (R) and coefficient (a)
Aiken's	Hyperbolic	Chl = exp[a + b*In (R)]	R = (L_W448/L_W551) a = 0.8933
Clark	Hyperbolic	Ln (chl) = a + b (R)	R = In[(LW443 + LW531)/(LW551)] a = 3.7656
Gordon	Hyperbolic + power	Chl = a (L_W551/L_W443)^b	a = 1.9333
NDCI	Hyperbolic	Ln (chl) = a (R) - b	R = [(LW443/LW448) – (LW551/LW488)] a = -3.1773

Montres-Hugo et al. (2008), the reflectance in each spectral channel was calculated as the ratio of the upwelling radiance L_u to the downwelling irradiance E_d:

$$R = \left[\frac{L_u}{E_d} \right] \quad (1)$$

With the completion of the optional measurement, a water sample was collected at 1 m below the water surface by a 51 Niskin bottle, transferred to a plastic carboy and put in the dark, prior to further processing in the laboratory, which took place approximately 24 h after the sampling. In the laboratory, chlorophyll-a was determined fluorometrically, on duplicated 200 ml samples, filtered onto GF/F filters and extracted for 24 h in the dark at 4°C in 90%.

Algorithms for chlorophyll-a estimation

Prior to Chl-a modelling from MODIS satellite data, radiometric correction, land and cloud masking are performed (Figure 3). Then, selected bands width of 443, 448, 531 and 551 µm are used to estimate chl-a concentrations (Table 1). In practice, chlorophyll-a concentration can be estimated by Gordon, Clark-3-bands, Normalized Difference Chlorophyll Index (NDCI) and Aiken's algorithms. The algorithms were used in a single or multiple bands of MODIS data based on hyperbolic and power function forms. This involves four algorithms which are evaluated in this work (Table 1). These algorithms involved Aiken's and NDCI algorithm (Aiken et al., 1995). Both algorithms are based on the concept of band ratio and

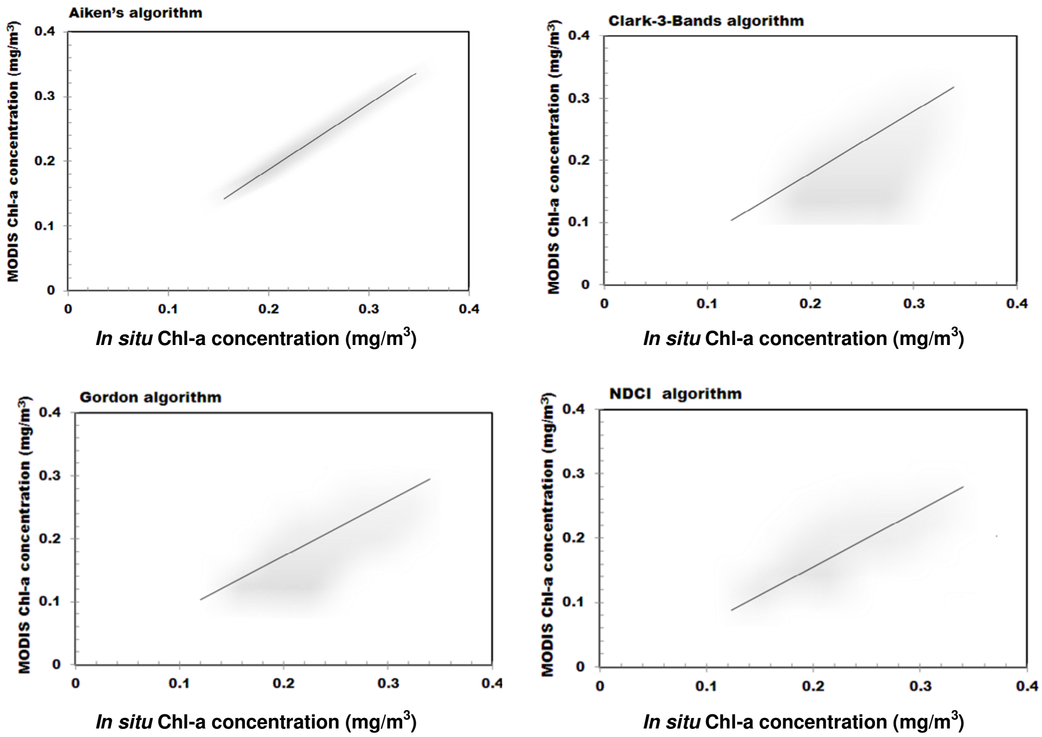

Figure 4. Regression models of different algorithms.

are having hyperbolic and power function form. The Aiken's hyperbolic model estimates chlorophyll by a hyperbolic function using two band ratio of bands 9 and 10. The Normalized Difference Chlorophyll Index (NDCI) algorithm however, implemented three bands as compared to the Aiken's algorithm. The existing coefficients in both algorithms are derived from the regression model of MODIS data and *in situ* measurements.

As for the satellite imagery, MODIS data were obtained from MODIS website (http://ladsweb.nascom.nasa.gov). MODIS data have a pixel of 1 km at nadir and composite images of several data over the region of interest for a given orbit. For the years 2002 until 2007, only the terra and aqua mode with 250 and 500 m were available. Geo-located and atmospheric corrected imagery products were collected between the study areas. Therefore, satellite scenes included coastal and oceanic domains. However, imagery corresponded to the scenes captured between 1000 - 1200 local time. For each pixel and wavelength (λ), remote sensing reflectances (R_{rs}) were derived from the normalized water leaving the radiance (Aiken et al., 1994; Pattiaratchi et al., 1994; O'Reilly et al., 1998; Montres-Hugo et al., 2008; Maged and Mazlan, 2010).

$$R_{rs}(\lambda) = \left[\frac{nL_w}{F_0(\lambda)} \right] \tag{2}$$

where F_0 is the extraterrestrial solar irradiance and L_w is the downwelling radiance. Validation of satellite derived chlorophyll-a concentration was carried out with *in situ* samples of chlorophyll-a fraction. Matching between field measurements of chlorophyll-a and MODIS satellite remote sensing indices of chlorophyll-a concentration was performed using statistical different regression model and 'root mean square error' (RMSE). Finally, root mean square of bias (RMS) was used to determine the level of algorithm accuracies by a comparison with *in situ* chlorophyll-a concentration. Further, the linear regression model was used to investigate the level of linearity of chlorophyll-a concentration estimation from MODIS data. The root mean square of bias equals

$$RMS = [N^{-1}\sum_{i=1}^{N}(Chl-a_i - Chl-a_{situ})^2]^{0.5} \tag{3}$$

where $Chl-a_i$ is the estimated amount from MODIS satellite data and $Chl-a_{situ}$ is the *in situ* measurements. Moreover, time integrations are performed to determine the possible improvement of RMS. In doing so, simulations and retrievals were performed within a two-month period, and for each grid point, the retrieved chlorophyll-a concentration was averaged in six days during the MODIS satellite passes.

RESULTS AND DISCUSSION

Regression model is used to discriminate between the Aiken, Clark-3-Bands and Gordon algorithm and the Normalized Difference Chlorophyll Index (NDCI) algorithms in order to determine the appropriate algorithm used in estimating chlorophyll-a concentration in Malaysian coastal waters (Figure 4). However, statistical

Table 2. Regression model r^2 values and their equations for different algorithms.

Algorithm	Regression equation	r^2
Aiken	$chl\text{-}a_{MODIS} = 1.10\ chl\text{-}a_{in\ situ} - 0.032$	0.95
Clark-3-Bands	$chl\text{-}a_{MODIS} = 1.05\ chl\text{-}a_{in\ situ} - 0.042$	0.69
Gordon	$chl\text{-}a_{MODIS} = 1.076\ chl\text{-}a_{in\ situ} - 0.046$	0.85
NDCI	$chl\text{-}a_{MODIS} = 0.82\ chl\text{-}a_{in\ situ} - 0.028$	0.83

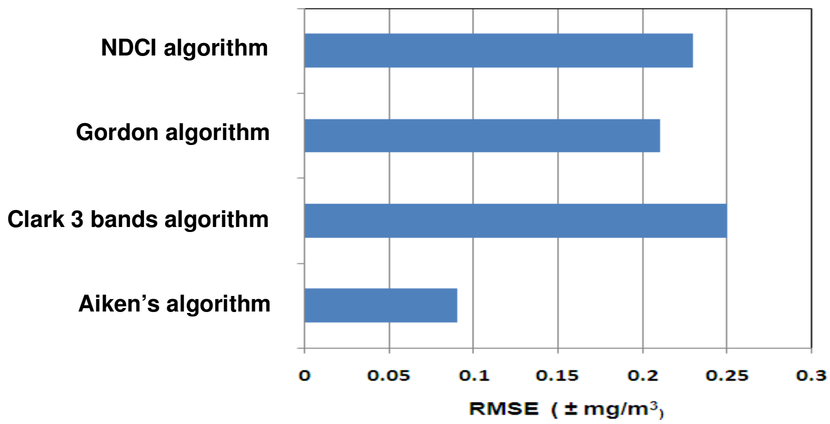

Figure 5. RMSE graphic bars for different algorithms.

r^2 varied among Aiken, Gordon, NDCI and Clark-3-band algorithms (Table 2).

Aiken's algorithm has the highest r^2 value of 0.95 than other algorithms. Further, the Aiken's algorithm illustrates RMSE of 0.09 mg/m^3 (Figure 5), thus performing a better estimation of Chl-a as compared to other algorithms. In fact, Aiken's algorithm is the exponential model, but it expresses a nonlinear relationship between *in situ* measurements and satellite MODIS data (Aiken et al., 1995). In this context, the nonlinear relationship has occurred due to the impact of real time closeness *in situ* measurements during or before satellite MODIS overpass. In this context, this model is particularly well suited for characterizing Chl-a concentration rate under limiting circumstances of real time closeness measurements (Maged and Mazlan, 2010). This study agrees with previous studies of Pattiaratchi et al. (1994), O'Reilly et al. (1998) and Montres-Hugo et al. (2008).

Figure 6 shows the synoptic maps of chlorophyll concentrations during northeast monsoon, inter-monsoon and southwest monsoon periods. In the northeast monsoon, the chlorophyll concentration pattern seems to have a homogenous variation along the east coast of Peninsular Malaysia. The maximum chlorophyll-a concentration value of 0.38 mg /m^3, however, is found in the northeast monsoon period (Figure 6a). In contrast, inter-monsoon period between southwest and northeast monsoon (September to October) suggests the lowest chlorophyll concentration value of 0.2 mg/m^3 as compared to other monsoon periods (Figure 6d). It is interesting to find that the chlorophyll concentration decreases gradually as it moved away from the coastline. This might explain the possibilities of upwelling occurrences along the coastline, especially during the northeast monsoon period (Zelina et al., 2000; Maged, 2009a). In fact, the highest rate of Chl-a concentration occurred near the coastal water, which indicates the high amount of nutrition that are received by coastal water due to water out flow from the estuary such as the mouth river of Kuala Terengganu as explained by Maged (2010).

In general, the spectral characteristics of chlorophyll-a can be mapped by MODIS satellite data. In fact, its spectral signature is located between blue and green wavelength of light spectrum. Different monsoon periods have different physical ocean parameters such as temperature, salinity and water masses (Pattiaratchi et al., 1994; O'Reilly et al., 1998; Montres-Hugo et al., 2008; Maged and Mazlan, 2010).

These parameters led to different spatial and seasonal variations of chlorophyll-a concentration along the east coast of peninsular Malaysia. This sort of pattern variation which is a function of monsoon wind cycle pattern can be named as vernal bloom. Consequently, it is parallel to seasonal cycle of terrestrial plants (O'Reilly et al., 1998). The cycle contains the period of exponential growth and then decreases abruptly, as a result of phytoplankton grazing by zooplankton. Further, the duration of this cycle is a short-period that ranged

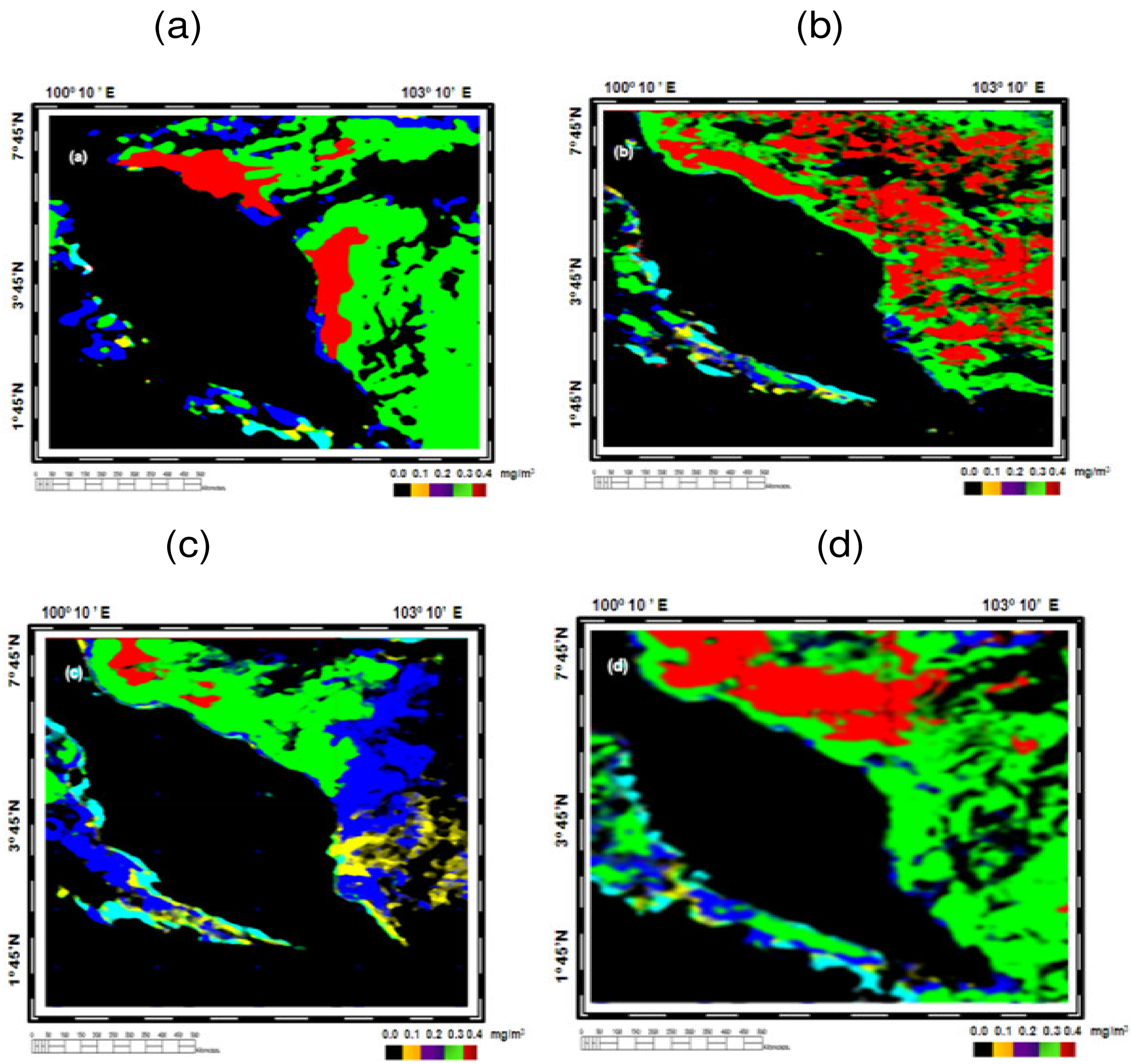

Figure 6. MODIS Chlorophyll-a concentration during (a) northeast monsoon, (b) inter-monsoon period (April), (c) southwest monsoon and (d) inter-monsoon (September to October).

between 1 and 2 weeks (Zelina et al., 2000).

Conclusions

This study has demonstrated a method to determine the appropriate algorithm for chlorophyll-a mapping from MODIS satellite data. The study shows that Aiken algorithm has the lowest RMSE of ±0.10 mg/m^3, while Clark-3-Bands, Gordon and Normalized Difference Chlorophyll Index (NDCI) algorithms have RMSE values of ±0.25, ±0.21 and ±0.23 mg/m^3, respectively. The results also showed that that the chlorophyll concentration decreased gradually as it moved away from the coastline and varied with different monsoon seasons. In the northeast monsoon, the maximum chlorophyll-a concentration value was 0.38 mg/m^3; however, inter-monsoon period between southwest and northeast monsoon (September to October) suggests the lowest chlorophyll concentration value of 0.2 mg/m^3 as compared to other monsoon periods. It can be concluded that MODIS satellite data are excellent in mapping chlorophyll concentration using Aiken algorithm.

REFERENCES

Aiken J, Moore GF, Trees CC, Hooker SB, Clark DK (1994). The SeaWiFS CZCS-type pigment algorithm. SeaWiFS Technical Report Series, NASA Technical Memorandum, 104, 566, 20, S.B. Hooker and E.R. Firestone (Eds.) (Greenbelt:NASA). pp. 34-38.

Ayman H, Nasr BM, Leithy El, Helmy AK (2007). Assessment of some water quality parameters using MODIS data along the Red Sea Coast, Egypt. ICGST-GVIP J., 7(3): 25-30.

Maged M (2001). TOPSAR wave spectra model and coastal erosion detection. Int. J. Appl. Earth Observ. Geoinf. Elsevier. 3(4): 357-365.

Maged M (2003). ERS-1 Modulation Transfer Function Impact on Shoreline Change Model. Int. J. Appl. Earth Observ. Geoinf., Elsevier, 4: 279-294.

Maged M (2009a). Linear algorithm for salinity distribution modelling from MODIS data. Proceedings of Geoscience and Remote Sensing Symposium, 2009. IEEE International, IGARSS 2009. University of Cape Town, Cape Town, South Africa, 12-17 July, 2009, 3: III-365 - III-368.

Maged M (2009b). Finite difference model for modeling sea surface current from RADARSAT-1 SAR data. Proceedings of Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009. University of Cape Town, Cape Town, South Africa, 12-17 July, 2009, 2: II-487 - II-490.

Maged M (2009c). 3D coastal bathymetry reconstruction using TOPSAR data . Proceedings of Geoscience and Remote Sensing Symposium, 2009 IEEE International,IGARSS 2009. University of Cape Town, Cape Town, South Africa, 12-17 July, 2009, 2: II-479 - II-482.

Maged M (2010). Examining the Least Square Method to Retrieve Sea Surface Salinity from MODIS Satellite Data.European J. Sci. Res. 40(3): 377-386.

Maged M, Ibrahim Z, Genderen JV (2002). Azimuth cut-off for significant wave height investigation along the coastal water of Kuala Terengganu, Malaysia. Int. J. Appl. Earth Observ. Geoinf., 4(3): 147-160.

Maged M, Mazaln H (2010). Utilization of MODIS Satellite Data for Modelling Chlorophyll Concentrations along Malaysian Coastal Waters. Am. J. Sci. Res. 8: 5-11.

Maged M, Mazlan H, Cracknell A (2009). 3D Reconstruction of coastal bathymetry from AIRSAR/POLSAR data. Chinese J. Oceanol. Limnol., 27(1): 117-123.

Montres-Hugo MA, Vernet M, Smith R, Carders K (2008). Phytoplankton Size-Structure on the Western Shelf of the Antarctic Peninsula: A Remote Sensing Approach, Int. J. Remote Sensing. 29(3-4): 801-829.

O'Reilly J, Maritorena S, Mitchell BG, Siegel DA, Carder KD, Garver SA, Kahru M, Mcclain C (1998). Ocean color algorithms for SeaWiFS. J. Geophysical Res. 103: 24937–24953.

Pattiaratchi C, Lavery P, Wyllie A, Hick P (1994). Estimates of water quality in coastal waters using multi date Landsat Thematic Mapper data. Int. J. Remote Sensing, 15: 1571–1584.

Zelina ZI, Arshad A, Lee SC, Japar SB, Law AT, Mustapha N, Maged MM (2000). East Coast of Peninsular Malaysia. IN: Seas at The Millenium: An Environmental Evaluation. Charles Sheppard (ed.). Elsevier Science LTD London,UK. pp. 345-359.