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A numerical method for retrieving sea surface salinity from MODIS satellite data

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This work presents a new approach for modeling sea surface salinity (SSS) from MODIS satellite data. In doing so, the least squares algorithm is used to retrieve SSS from multi MODIS bands data. Thus, the basic linear model has been solved by using least square estimators. *In situ* measurements are collected along the east coast of peninsular Malaysia by using hydrolab instrument. The study shows that homogenous offshore sea surface salinity as compared with onshore SSS variations. The onshore SSS are ranged between 28.5 and 29.5 psu whereas the offshore SSS variations have maximum value of 33.8 psu. The results also show a good correlation between *in situ* SSS measurements and the SSS that is retrieved from MODIS satellite data with high r^2 of 0.97 and RMS of bias value of ±0.37 psu. It can be said that least squares method can be used to provide a new algorithm for SSS retrieval from MODIS satellite data.

Key words: Sea surface salinity, moderate-resolution imaging spectrometer satellite data, least square estimators, linear model.

INTRODUCTION

Sea surface salinity (SSS) retrieval from satellite data is a major challenge. Indeed, dissolved salts, suspended substances have a major impacts on the the electromagnetic radiation attenuation outside the visible spectra range (Wong et al., 2007; Marghany, 2009; Marghany et al., 2010a). In this context, the electromagnetic wavelength larger than 700 nm is increasingly absorbed whereas the wavelength less than 300 nm is scattered by non-absorbing particles such as zooplankton, suspended sediments and dissolved salts (Ellison et al., 1998). *In situ* sea surface salinity (SSS) measurements, nevertheless, acquired by buoys and oceanographic or commercial ships, remain sparse and irregular, with large parts of the global ocean never sampled. In these circumstances, scientists have paid a great attention to utilize satellite data for SSS retrieval (Klein and Swift, 1997; Ellison et al., 1998; Maes and Behringer, 2000; Gabarro, 2004; Burrage et al., 2008). In this context, Wong et al. (2007) introduced linear algorithm to retrieve SSS from Aqua/MODIS level 1B reflectance data with 250 and 500 m spatial resolution.

In spite of these there are no works to correlate sea surface salinity (SSS) with MODIS reflectance; Wong et al. (2007) have assumed that there is a linear relationship between SSS and MODIS reflectance of band 1 to band 7. They stated that the linear algorithm provides accurate SSS retrieving from Aqua/MODIS level 1B reflectance data with root mean square error of 1.63 psu. In addition, they found that the principle component analysis (PCA) has poor accuracy for SSS retrieving than linear empirical algorithm. Recently, Ahn et al. (2008) and Palacios et al. (2009) have derived SSS using colored dissolved organic matter concentration, (a_{CDOM}) from optical satellite data. In fact, Hu et al. (2004) have suggested that SSS can correlate linearly or inversely with CDOM. In this circumstances, Ahn et al. (2008) have developed robust and proper regional algorithms from large *in situ* measurements of apparent and inherent optical properties (that is remote sensing reflectance, R_{rs} and absorption coefficient of colored dissolved organic matter, a_{CDOM}) to derive salinity using SeaWiFS images. Further, Palacios et al. (2009) stated that light absorption by

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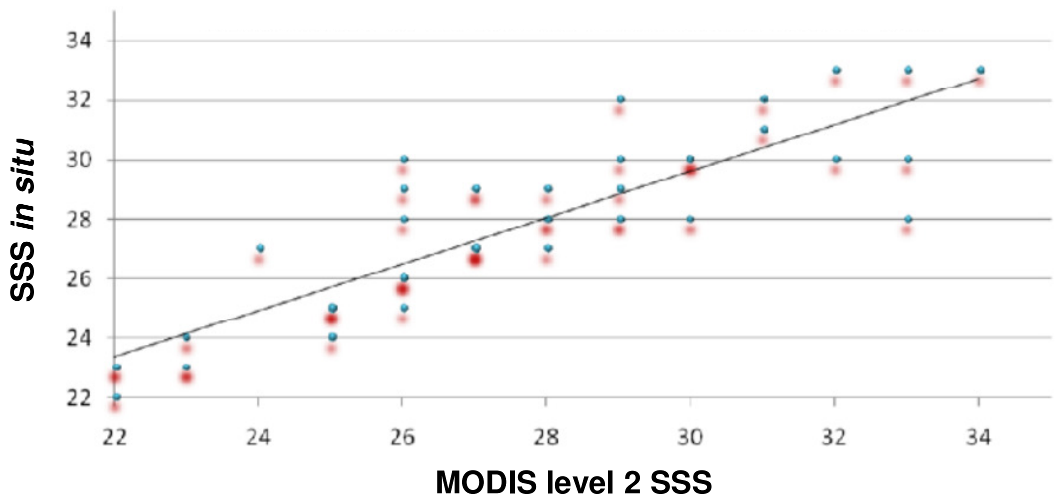

Figure 1. Regression analysis between MODIS SSS and *in situ* measurements form.
Source: Salah et al. (2010a).

chromophoric dissolved organic matter (a_{CDOM}) is inversely proportional to salinity and linear because of conservative mixing of CDOM-rich terrestrial runoff with surrounding ocean water. In this context, Ahn et al. (2008) established the robust algorithm based on the absorption coefficients of CDOM, *in situ* measurements of salinity that was made at 400, 412, 443 and 490 nm.

Similarly, Palacios et al. (2009) developed synthetic salinity algorithm simple linear (salinity versus a_{CDOM}) and multiple linear (salinity and temperature versus a_{CDOM}) algorithms were applied to MODIS 250 m resolution data layers of sea surface temperature and absorption by colored dissolved and detrital matter (a_{CODM}) estimated at 350 and 412 nm from the Garver-Siegel-Maritorena model version 1 algorithm. Ahn et al. (2008) found that the CDOM absorption at 400 nm was better inversely correlated (r^2 = 0.86) with salinity than at 412, 443 and 490 nm (r^2 = 0.85 to 0.66), and this correlation corresponded best with an exponential (r^2 = 0.98) rather than a linear function of salinity measured in a variety of water types from this and other regions. In this context, Palacios et al. (2009) stated that light absorption by chromophoric dissolved organic matter (a_{CDOM}) is inversely proportional to salinity and linear because of conservative mixing of CDOM-rich terrestrial runoff with surrounding ocean water using MODIS satellite data.

The study of Palacios et al. (2009) showed high correlation using MODIS during both downwelling (simple, β_1 = 0.95 and r^2 = 0.89; multiple, β_1 = 0.92 and r^2 = 0.89) and upwelling periods (simple, β_1 = 1.26 and r^2 = 0.85; multiple, β_1 = 1.10 and r^2 = 0.87) using the 412 nm data layer. Both studies of Ahn et al. (2008) and Palacios et al. (2009) have agreed that SSS can be derived using optical satellite data based on absorption coefficient of colored dissolved organic matter, a_{CDOM}. Marghany (2009a, 2010) and Marghany et al. (2010a) have implement the least square methods to retrieve SSS salinity from MODIS satellite data. Nevertheless, they implemented the similar least square methods coefficient parameters with different season data. Indeed, these parameters must be changed from season to season due to seasonal variation of SSS. On contrary, Salah et al. (2010a) claimed a new approach for SSS retrieving from MODIS data using linear regression model and polynomial formula. This technique, however, is considered a conventional method as compared to studies of Hu et al. (2004), Wong et al. (2004), Ahn et al. (2008), Palacios et al. (2009), Marghany (2009, 2010) and Marghany et al. (2010). Consequently, Salah et al. (2010a) implemented a fallacious linear regression equation to estimate SSS with RMSE of 1.5 psu. Further, Figure 1 which is captured from Salah et al. (2010a) study does not show r^2 of 0.91 and RMSE of 1.5 psu. In addition, Salah et al. (2010a) have also claimed that polynomial algorithm provides a similar SSS as well as linear regression model. Conversely, that study does not show any output results derived using polynomial algorithm.

Continuously, Salah et al. (2010b) used an erroneous formula to retrieve sea surface salinity in the South China Sea coastal waters, along the coastal water of Semporna. Salah et al. (2010b), however, used the same results of the study of Salah et al. (2010a) and claimed that multi linear and minnet algorithms provide promising precise SSS pattern. Further, Semporna does not lie in coastal waters of the South China Sea. They used the *in situ* data that collected along east coast of Sabah; Semporna, to retrieve seasonal SSS changes in east coast of Peninsular Malaysia. However, Semporna is considered as small bay where any SSS *in situ* measurements cannot be used to retrieve SSS along east coast of Malaysia due to different physical geography

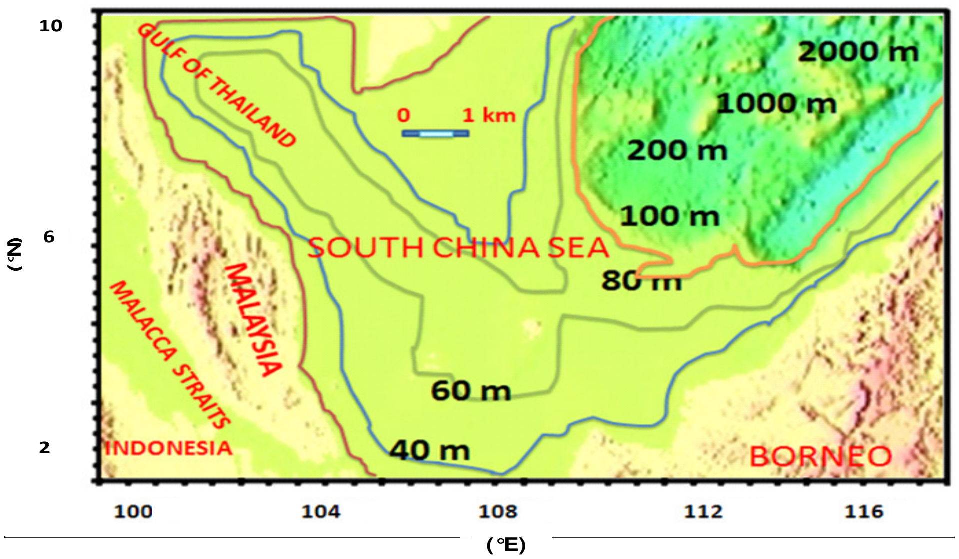

Figure 2. Location of the South China Sea and its bathymetry spatial variations.

geography locations and sea surface characteristics. In general, both Salah et al. (2010a, b) studies show contradictory SSS pattern with diametrically opposed formulas. These types of studies provide a confusing and wrong information for SSS retrieving from MODIS satellite data, although *in situ* measurements are very costly.

The main problem to retrieve SSS from remote sensing data such as the soil moisture and ocean salinity (SMOS) and Aquarius satellite missions is bright temperature. Because of the difficulties to acquire brightness temperature from L-band satellite radiometric measurements. Indeed, L-band has limited resolution (typically 30 to 100 km) and nearby land can impure L-band measurements over the coastal zone. This work has hypothesized that there is a direct method to retrieve SSS from satellite data without relying on brightness temperature. In this context, a linear model can be used as semiautomatic algorithm to estimate SSS from optical satellite data such as MODIS. In addition, utilizing of a least square method can improve the accuracy of SSS retrieval from optical satellite data. In doing so, this study extends the previous theory of linear relationship between satellite pixel reflectance value variations in different bands with SSS by deriving a different coefficient values of linear algorithm using moderate-resolution imaging spectrometer (MODIS) that is, the Aqua/MODIS data level IB reflectance satellite data.

METHODOLOGY

Data set

MODIS data acquired in this study were derived from MODIS/Aqua sensor involved high radiometric sensitivity data in 36 spectral bands (Marghany and Mazlan, 2010b). According to Wong et al. (2007) these data were ranged between 0.4 to 14.4 µm. In addition, MODIS data have 36 bands: the first two bands are imaged at a nominal resolution of 250 m; the next five bands have nominal resolution of 500 m; and the remaining 29 bands particularly have 1 km resolution. Further, MODIS data have 4 levels which are: level 0, 1A, 1B, 2, 3 and 4. Level 0 raw instrument data at original resolution, time ordered, with duplicate packets removed. Level 1A is a reconstructed unprocessed instrument/payload data at full resolution, any and all communications artefacts (for example synchronization frames, communications headers) removed. Level 1B is a Level 1A data that have been processed to sensor units and radiometrically corrected and geolocated. Twenty four sets of Aqua/MODIS level 1B images are acquired during the *in situ* salinity measurements. In addition, Level 2 is a derived geophysical variable at the same resolution and location as the Level 1 source data. Level 3 is a variable mapped on uniform space-time grid scales, usually with some completeness and consistency.

Level 4 is a model output or results from analyses of lower level data (that is, variables derived from multiple measurements) (Hu et al., 2004).

Study area and *in situ* measurements

Study area is located along the east coast of Penssiular Malaysia as part of the South China Sea (SCS) (Figure 2). According to Marghany (2009b) the location of the South China Sea (SCS) where it is considered as an equatorial, semi-enclosed sea with a complex topography that includes large shallow regions (Marghany and Mazlan, 2010b; Marghany et al., 2010b). The SCS is located between the Asian continent, Borneo, the Philippines and Taiwan (Figure 2). The northeastern part adjoins a deep sea basin, while the southern part is a shelf sea with depths less than 200 m. The study is conducted in two phases: (i) On September 2002 along the coastal waters of Kuala Terengganu and (ii) on October 2003 in Phang coastal waters, Malaysia (Figure 3). In doing so, more than 100 sampling locations are chosen (Figure 3). The field cruises are conducted separately, area by area on the east coast of Peninsular Malaysia. In fact, it is a major challenge to cover a large scale area over than 700 km^2 in short period using conventional techniques.

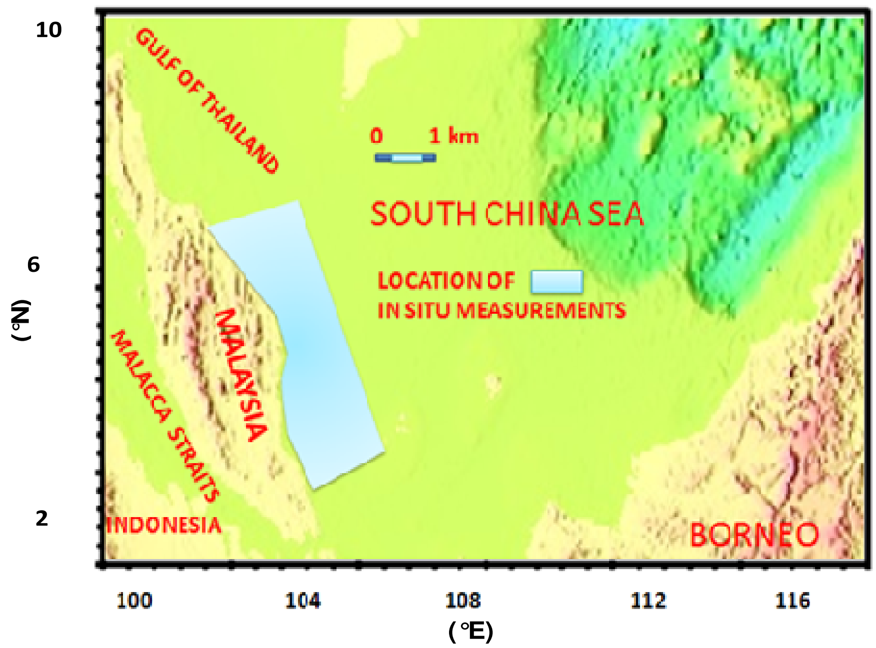

Figure 3. Sampling locations.

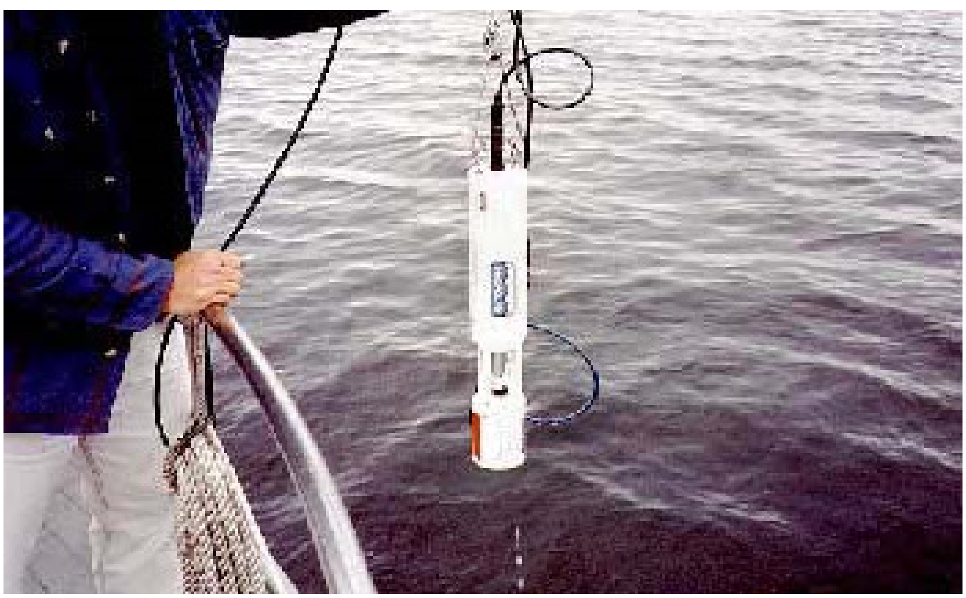

Figure 4. Hydrolab used in this study.

The hydrolab equipment is used to acquire vertical water salinity profiles (Figure 4). Every field cruise has been conducted on 6 days in the east coast of Malaysia.

For this study the *in situ* surface salinity (1 m below sea surface) data are used. In fact, it is expected to have a higher correlation with MODIS reflectance data than middle and bottom salinity column measurements. These data are used to validate the sea surface salinity distributions that is derived from MODIS data. *In situ* measurements are collected near real time of MODIS satellite data overpass.

Sea surface salinity retrieving using least square algorithm

Here, we present the theoretical model of split window method that relates MODIS sea surface salinity with *in situ* salinity measured by thermal infrared sensors, these include multi-channel methods (Figure 5). We assume the MODIS image radiance I within multi-channels i have a linear relationship with measured sea surface salinity (SSS). According to Marghany (2009a, 2010) and

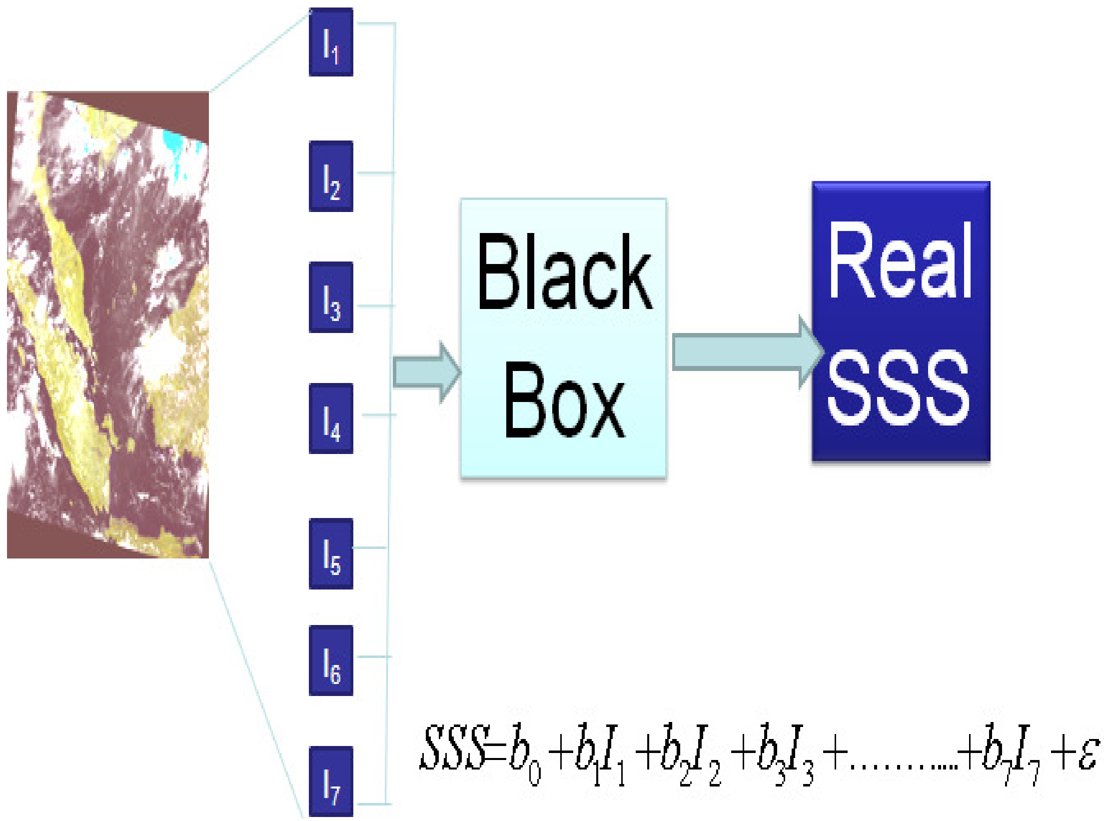

Figure 5. Flow chart for sea surface salinity (SSS) retrieving concept from MODIS data.

Marghany et al. (2010a), a useful extension of linear function of *k* channels as in:

$$SSSMODIS_i = \beta_0 + \sum_{i=1}^{k} \beta_j I_{ij} \qquad I = 1, 2, \ldots, n \qquad (1)$$

Where the retrieval sea surface salinity $(SSSMODIS)_i$ in scalar notation, from MODIS data, the least squares estimators of the regression coefficients are $\beta_0, \beta_1, \ldots\ldots\ldots, \beta_k$ and *k* is a number of selected MODIS radiance bands which equals 7 bands. Therefore, the fitted regression model to retrieve the sea surface salinity from MODIS data (SSSMODIS) is:

$$SSSMODIS = I\,\beta \qquad (2)$$

Where β is the ordinary least squares estimator of b to distinguish it from other estimators based on the least squares idea. According to Marghany et al. (2010a) β is given by:

$$\beta = (I'\,I)^{-1}\, I'\, SSS \qquad (3)$$

In general, SSS is an (*n x 1*) vector of the sea surface salinity (SSS) observations from MODIS radiance data I which is and (*n x p*) matrix of the levels of independent variables. In addition, I′ SSS is a (*p x 1*) column vector (Marghany, 2010). In this form it is easy to see that I′ I is a (*p x p*) symmetric matrix (Marghany et al., 2010a). The matrix form of normal equations is identical to scalar form. Writing out Equation 3 in detail, we obtain:

$$\begin{bmatrix} n & \sum_{i=1}^{n} I_{i1} & \sum_{i=1}^{n} I_{i2} & \cdots & \sum_{i=1}^{n} I_{ik} \\ \sum_{i=1}^{n} I_{i1} & \sum_{i=1}^{n} I_{i1}^2 & \sum_{i=1}^{n} I_{i1} I_{i2} & \cdots & \sum_{i=1}^{n} I_{i1} I_{ik} \\ \vdots & \vdots & \vdots & & \vdots \\ \sum_{i=1}^{n} I_{ik} & \sum_{i=1}^{n} I_{ik} I_{i1} & \sum_{i=1}^{n} I_{ik} I_{i2} & & \sum_{i=1}^{n} I_{ik}^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} SSS_i \\ \sum_{i=1}^{n} I_{i1} SSS_i \\ \vdots \\ \sum_{i=1}^{n} I_{ik} SSS_i \end{bmatrix} \qquad (4)$$

To find the vector of least squares estimators b, that minimizes:

$$S(b) = \sum_{i=1}^{n} \varepsilon_i^2 = \varepsilon'\,\varepsilon = (SSS - Ib)'(SSS - Ib) \qquad (5)$$

Where b is a (*p x 1*) vector of the regression coefficients and ε is an (*n x 1*) vector of random errors. Note that S(b) may be expressed:

$$S(b) = SSS'\,SSS - 2b'\,I'\,SSS + b'\,I'\,I\,b \qquad (6)$$

Since b′I′SSS is a (1 x 1) matrix or sclar and its transpose (b′I′SSS)′

= SSS′Ib is the same scalar. The least squares estimators must satisfy:

$$\frac{\partial S}{\partial b}\Big|_{\beta} = -2\, I'\, SSS + 2\, I'\, I\, \beta = 0 \quad (7)$$

The function S is to be minimized with respect to $b_0, b_1, b_2, ..., b_k$. The least squares estimators, say $\beta_0, \beta_1, ..., \beta_k$, must satisfy:

$$\frac{\partial S}{\partial b_0}\Big|_{\beta_0,\beta_1,....,\beta_k} = -2\sum_{i=1}^{n}(SSS_i - \beta_0 - \sum_{j=1}^{k}\beta_j I_{ij}) = 0 \quad , \quad (8)$$

and,

$$\frac{\partial S}{\partial b_j}\Big|_{\beta_0,\beta_1,....,\beta_k} = -2\sum_{i=1}^{n}(SSS_i - \beta_0 - \sum_{j=1}^{k}\beta_j I_{ij})I_{ij} = 0 \quad ,$$

j=1,2,……,k (9)

It is necessary that the least squares estimators $\beta_0, \beta_1, ..., \beta_k$ satisfy the equations given by the *k* first partial derivatives $\frac{\partial S}{\partial b_j} = 0$, *I = 1, 2, 3,…..n* and *j = 1, 2, 3,…..k.*

According to Marghany (2009a), the least squares function (*S*) is:

$$S = \sum_{i=1}^{n}\varepsilon_i^2 = \sum_{i=1}^{n}(SSS_i - b_0 - \sum_{j=1}^{k} b_j I_{ij})^2 \quad (10)$$

The unknown parameters in Equation 10, that are b_0 and b_i may be estimated by a general least square iterative algorithm (Marghany et al., 2010a). Marghany (2009a) stated that the general model is of the form of Equation 10 and that there are *n* observations (*n* ≥ *k*) on the response variable are available, say $SSS_1, SSS_2, ..., SSS_n$. Along with each observed response SSS_i, we will have an observation on each regressor variable and let I_{ij} denote the *ith* observation of MODIS radians selected bands or level of MODIS radiance variable I_i. We assume that the error term ε in the model has mean zero and constant variance σ^2, that is, $E(\varepsilon) = 0$ and $\mathrm{var}(\varepsilon) = \sigma^2$, and the $\{\varepsilon_i\}$ are uncorrelated random variables. The model, written in terms of the SSS_i observations, is:

$$SSS_i = b_0 + b_1 I_{i1} + b_2 I_{i2} + b_3 I_{i3} + ... + b_k I_{ik} + \varepsilon_i$$

$$SSS_i = b_0 + \sum_{j=1}^{k} b_j I_{ij} + \varepsilon_i \quad , I = 1, 2, 3,…………,n \quad (11)$$

It is simpler to solve the normal equations if they are expressed in matrix notation. We now give a matrix development of the normal equations that parallels the development of Equation 11. The Equation 11 may be written in matrix notation as:

SSS = Ib + ε (12)

Where,

$$SSS = \begin{bmatrix} SSS_1 \\ SSS_2 \\ : \\ : \\ SSS_n \end{bmatrix}, \quad I = \begin{bmatrix} 1 & I_{11} & I_{12} & ... & I_{1k} \\ 1 & I_{21} & I_{22} & ... & I_{2k} \\ : & : & : & & : \\ 1 & I_{n1} & I_{n2} & ... & I_{nk} \end{bmatrix}$$

$$b = \begin{bmatrix} b_0 \\ b_1 \\ : \\ : \\ b_k \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ : \\ : \\ \varepsilon_n \end{bmatrix},$$

Following Sonia et al. (2007), ε errors that represents the difference between retrieved and *in situ* SSS are computed within 10 km grid point interval and then averaged over all grid points having the same range of distance to coast, where the bias ε on the retrieved $SSSMODIS$ is given by:

$$\varepsilon = \frac{\sum_{i=1}^{N}(SSSMODIS - SSS_{situ})}{N} \quad (13)$$

Where $SSSMODIS$ is the retrieved sea surface salinity from MODIS satellite data, SSS_{situ} is the reference sea surface salinity on grid point *i* and *N* is the number of grid points. Then, the empirical formula of $SSSMODIS$ (psu) which is based on Equations 1, 12 and 13 for month of September 2002 is:

$SSSMODIS$ (psu) = 27.65 + 0.2 I_1 - 21.11 I_2 + 14.23 I_3 + 62.12 I_4 + 148.32 I_5 + 122.03 I_6 + - 11.41 I_7 ± 0.4 (14)

For month of October 2003, empirical formula of $SSSMODIS$ (psu) is given by:

$SSSMODIS$ (psu) = 26.89 + 0.13 I_1 - 19.31 I_2 + 12.97 I_3 +

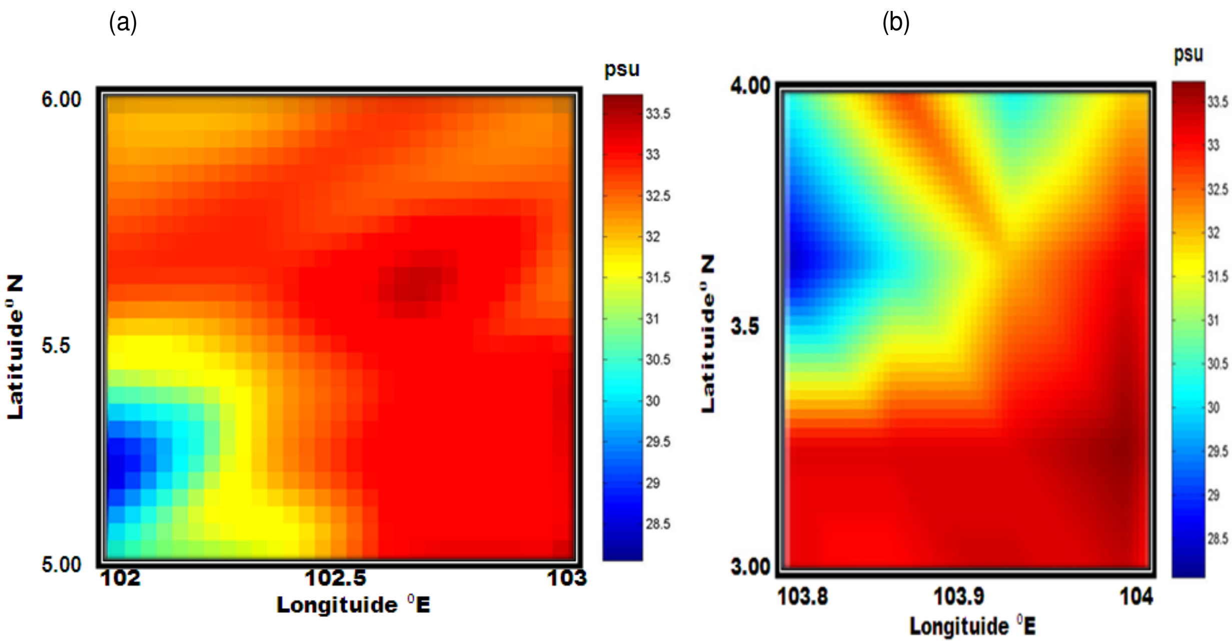

Figure 6. *In situ* measurements during (a) September 2002 and (b) October 2003.

$$58.74\ I_4 + 134.21\ I_5 + 119.93\ I_6 + - 9.78\ I_7 \pm 0.26 \qquad (15)$$

Following Marghany et al. (2010), root mean square of bias (RMS) is used to determine the level of algorithm accuracy by comparing with *in situ* sea surface salinity. Further, linear regression model used to investigate the level of linearity of sea surface salinity estimation from MODIS data. The root mean square of bias equals:

$$RMS = [N^{-1}\sum_{i=1}^{N}(SSSMODIS - SSS_{situ})^2]^{0.5} \qquad (16)$$

The time integrations is 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 SSS was averaged over six days during the MODIS satellite different times over passes.

RESULTS AND DISCUSSION

Sea surface salinity retrieved from hydrolap measurements during the inter-monsoon period of September 2002 and October 2003 are illustrated in Figure 6. In September 2002, the water salinity ranges between 28.5 to 33.6 psu whereas in October 2003, the water salinity ranges between 29.5 to 33.0 psu. Both filed observations show the onshore waters salinity are lower than offshore. The onshore water salinity is ranged between 28.5 to 30 psu during September 2002. In October 2003, however, the onshore water salinity is ranged between 29.5 to 31.0 psu. It is clear that the offshore water salinity is higher than onshore within constant value of 33.5 psu in September 2002 and October 2003, respectively. Further, both September 2002 and October 2003 dominated by tongue of low water salinity penetration of 28.5 and 29.5 psu, respectively along the coastal water. The sea surface salinity derived modeled from MODIS data using multi-linear regression model is shown in Figure 7. Clearly, the existence model provides fuzzy sea surface salinity. In early stage, sea surface salinity estimated directly using multi-linear regression model are not accurate with RMS of ± 20.34 psu with r^2 of 0.1 (Figure 7b). Figure 8 shows the sea surface salinity retrieved from MODIS data in September 2002 and October 2003, respectively. It is observed that the offshore water salinity is higher than onshore.

The homogenous offshore water salinity pattern occurred in both September 2002 and October 2003 with maximum salinity value of 33.00 psu in September 2002 and 33.8 psu in October 2003. Both *in situ* measurements and modeled SSS from MODIS data are agreed that the occurrences of tongue of low water salinity penetration along the coastal waters. This may be attributed to the proximity of nearshore waters are closed to the rivers such as Kuala Ternggganu river. The maximum amount of rainfall in the September 2002 and October 2003 are 150 and 300 mm, respectively. This high amount of rainfall is not only diluting the salinity of the surface water but also cause a high amount of fresh water discharges from the rivers that are located along the east coast of Malaysian waters into the South China Sea. This agrees with the studies of Wrytki (1969), Maged (1994), Maged et al. (1996) and Zelina et al. (2000).

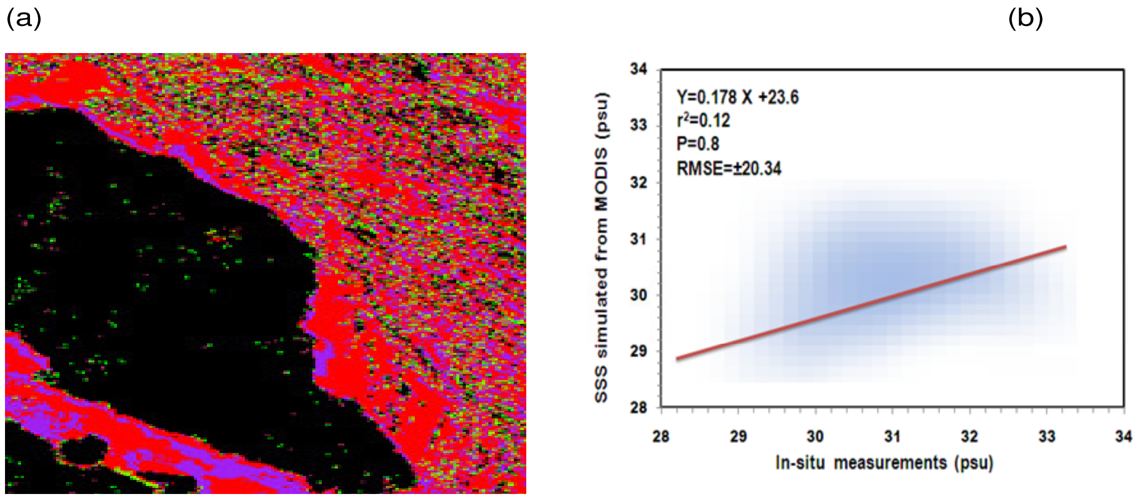

Figure 7. Modeled sea surface salinity using (a) multi-linear regression model and (b) regression analysis with *in-situ* measurements.

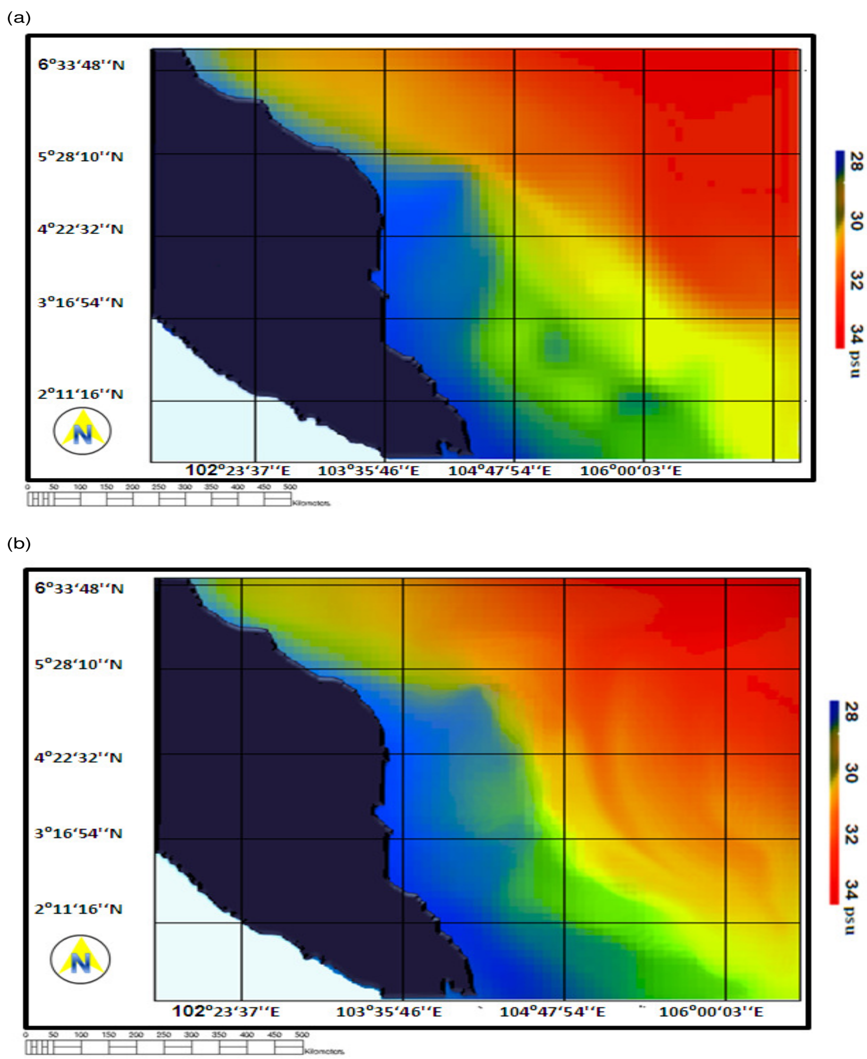

Figure 8. Sea surface salinity estimated from MODIS data (a) September 2002 and (b) October 2003.

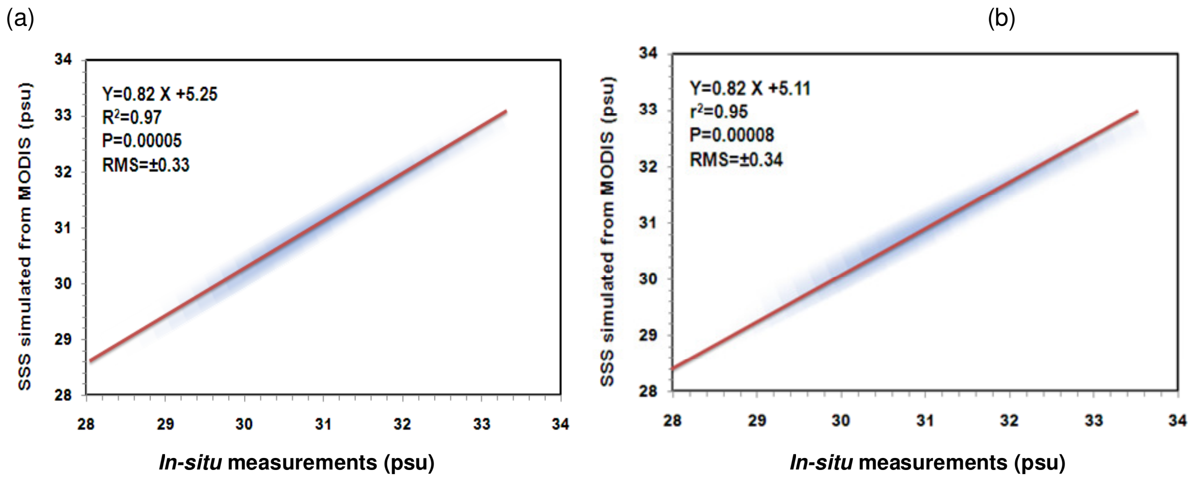

Figure 9. Regression model between *in situ* SSS and SSS modeled from MODIS data during September 2002 and (b) October 2003.

Figure 9 shows the comparison between *in situ* sea surface salinity measurements and SSS modeled from MODIS data. Regression model shows that SSS modeled using least square algorithm is in good agreement with *in situ* data measurements. The degree of correlation is a function of r^2, probability (p) and root mean square of bias (RMS).

The relationship between simulated SSS from MODIS data and *in situ* data shows positive correlation as r^2 value is 0.97, 0.95 with p of 0.00005, 0.00008 and RMS value of ± 0.33 psu and ± 0.33 psu during September 2002 and (b) October 2003, respectively. However, this result does not agree with Wong et al. (2007). In fact, Wong et al. (2007) have acquired RMS ±1.63 that is higher than RMS of this study. This could be attributed to that Wong et al. (2007) have been implemented linear regression model without concerning the residual error occurred due to uncorrelated relationship between MODIS radiance data and *in situ* measurements. There is a great contrary between recent study and Salah et al. (2010a, b). Indeed, Salah et al. (2010 a, b) studies did not derive a real sea surface salinity from MODIS data. Further, they implemented improper equation parameters and wide of the mark of geographical location for *in situ* measurements as reported on Salah et al. (2010b). Crooked field measurements will produce confusing pattern of sea surface salinity. Without a doubt, least square algorithm requires accurate input parameters to be run through MODIS data. Further, precise results of sea surface salinity in recent study can be explained as: using multiple MODIS bands that is, 1 to 7 bands is a useful extension of linear regression model is the case where SSS is linear function of 7 independent bands. Such a practical is particularly useful when modeling SSS from MODIS data.

Further, using least squares method derive a curve that minimizes the discrepancy between estimated SSS from MODIS data and *in situ* data. This means that using a new approach based on least squares method would be to minimize the sum of the residual errors for the estimating SSS from MODIS data. Further, this study shows the possibilities of direct retrieving of the SSS from visual bands of MODIS satellite data without utilizing such parameter of colored dissolved organic matter, a_{CDOM} (Ahn et al., 2008; Palacios et al. (2009). This work confirms the studies of Marghany (2009, 2010) and Marghany et al. (2010). Additionally, MODIS satellite shows precise promising for modelling sea surface salinity instead of using soil moisture and ocean salinity (SMOS) and Aquarius satellite missions. As well, SMOS provides an SSS based on surface brightness temperatures with a precision over the open ocean of 0.2 practical salinity units (psu) in 200 × 200 km boxes on a ten-day average (Ellison et al., 1998; Maes and Behringer, 2000; Sonia et al., 2007). Generally, monitoring surface brightness temperatures, however, from L-band satellite radiometric measurements is particularly challenging because of their limited resolution (typically 30 to 100 km) and L-band measurements over the coastal ocean are contaminated by the nearby land. In fact, recent global simulations of L-band land brightness temperatures showed a range of about 140 to 300 K, compared to approximately 100 K for the ocean (Sonia et al., 2007).

CONCLUSIONS

This study has demonstrated a new approach for deriving new algorithm to retrieve sea surface salinity from optical remote sensing satellite data such as MODIS. In doing so, least squares method is used to derive a new SSS algorithm for MODIS satellite data. This algorithm involves the residual error and least squares estimator to acquire accurate results. The results show that tongue of low water salinity penetration of 28.5 and 29.5 psu during September and October, occurred respectively, along the coastal waters. The study shows a homogenous offshore sea surface salinity with maximum value of 33.8 psu. Further, result shows the high correlation coefficient at r^2 of 0.97 and RMS of bias value of ±0.33 psu. In conclusion, a new formula of SSS has improved mapping of SSS from MODIS data. This new approach can be used as a tool to estimate SSS.

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