Chapter 4

IMPROVED ALGORITHMS FOR TOTAL SUSPENDED MATTER (TSM) ESTIMATION

4.1 INTRODUCTION

Process such as tides and waves, river discharge, wind stress and turbidity currents modulate the transport and distribution of suspended sediments in coastal environment. It has been demonstrated by a large number of studies that satellite based remote sensing can be effectively used in detection and quantification of total suspended matter in coastal seas (e.g. Klemas et al. 1974, Tassan and Sturm 1986, Ritchie et al. 1990, Chauhan et al., 1996). The study of suspended matter has an ecological importance because it is the main carrier of various inorganic and organic substances (including pollutants) and becomes the main substrata for biogeochemical processes (Doerfler et al., 1989). Suspended sediments also affect the penetration of light and the transport of nutrients, shoreline morphology, among other processes.

Remote sensing of oceanic and coastal waters depends upon the interaction of light with optically active water constituents, such as phytoplankton, total suspended matter and dissolved organic matter, and dissolved organic matter, also known as yellow substance (Sathyendranath et al., 1989). Seawater is classified as case I and case II depending on whether concentration of optically active water constituents is correlated among
themselves or not (Gordon and Morel, 1983). Ocean represents typical case 1 water, where only phytoplankton dominates as optically active water constituent.

Coastal waters are often known as case II water, as water constituents other than phytoplankton, such as inorganic suspended matter originating from river drainage and dissolved organic matter (or yellow substance) also contributes to reflected spectrum of the incoming light field. It has been observed that often all the three main constituents of coastal waters are uncorrelated to each other; however there can be situations, where these parameters may exhibit large spatial and temporal variations as a result of local phenomenon such as bottom re-suspension and urban and industrial effluents (Tassan, 1994). Therefore estimation of individual parameter becomes a difficult task in case II waters, largely due to uncorrelated behavior of water constituents.

Ocean color experiments using satellite sensors such as CZCS, IRS-P3 MOS-B and SeaWiFS have been used for detecting suspended matter (Viollier and Sturm 1984, Tassan and Sturm, 1986). A large number of sediment algorithms have been proposed to quantify total suspended matter using these ocean color payloads (Tassan and Sturm, 1986, Tassan, 1994, Neumann et al., 1995, Chauhan et al. 1997). The IRS-P4 Ocean color Monitor (OCM) sensor, launched by Indian Space Research Organization (ISRO) is a second-generation ocean color sensor. With a spatial resolution of 360 meter and suitably selected spectral bands with high SNR and narrow spectral channels, OCM is among one of the most ideal sensors for the analysis of coastal waters constituents.

The objective of the investigations described here is to find a robust algorithm for the estimation of total suspended matter (TSM) concentration in coastal waters around the Indian peninsular region using IRS-P4 OCM satellite data. In the present study, we
demonstrate the use of a three component model of ocean color proposed by Sathyendranath et al., (1989) to simulate a large set of sub-surface reflectance values by independently varying the concentration of chlorophyll, suspended matter and yellow substance over the concentration range generally encountered in coastal waters. The simulated data set was subsequently used to construct the estimation algorithm for total suspended matter (TSM) in the presence of uncorrelated phytoplankton and yellow substance. The developed algorithm was tested on an independent simulated data set and subsequently on the IRS-P4 OCM images of the Arabian Sea.

4.2 OCEAN COLOR REFLECTANCE MODEL

The use of an analytical ocean color model to relate reflectance to TSM via inherent optical properties facilitates extension to a general multi sensor approach (e.g. to include AVHRR, SeaWiFS, MOS, etc.) and permits an estimation of the errors in simple TSM-reflectance formulae introduced by variability in other water constituents, such as chlorophyll and yellow substance. In this study the analytical model has been applied to model reflectance corresponding to IRS-P4 OCM bands for varying range of TSM chlorophyll and yellow substance concentrations. The upwelling radiance leaving the ocean is a complicated mix of signals caused by many components. The major contribution arises from the following: absorption by molecules and particulates. The subsurface-irradiance reflectance \( R \), ratio of the upwelling to the downwelling irradiance just below the sea surface, can be modeled by a series relation proposed by Gordon et al., (1975) using Monte Carlo method by

\[
\sum_{m=0}^{3} r_m \left[ \frac{B_B}{A+B_B} \right]^m
\]
Where, \( A \) is total absorption coefficient, \( B_b \) is total backscattering coefficient, both are spectrally dependent functions, equation (1) was further simplified by Morel and Prieur (1997) and reduced to the following form, for values of \( b_h/a \) up to \( \| 0.25 \).

\[
R = 0.33 \left( \frac{B_b}{A} \right) \quad (2)
\]

The inherent optical properties of total absorption coefficient, \( A \) and total backscattering coefficient \( B_b \) are in turn related to the water constituents such as total suspended matter concentration \( S \), chlorophyll-a concentration \( C \) and yellow substance absorption at 400nm, \( Y \), via following equations,

\[
A(\lambda) = A_w(\lambda) + a_c(\lambda) + C + a_y(\lambda)S + a_y(\lambda) \quad (3)
\]

\[
B_b(\lambda) = -r_wB_w(\lambda) + r_cB_c(\lambda) + r_sB_s(\lambda) \quad (4)
\]

Where, \( A_w(x) \) and \( B_w(x) \) are absorption and backscattering coefficients, respectively due to water, \( a \) is specific absorption coefficient (m\(^{-1} \) per unit concentration), \( r \) is backscattering ratio, \( B \) is volume scattering coefficient (m\(^{-1} \)), and suffix c, s and y corresponds to chlorophyll-a, total suspended matter and yellow substance absorption respectively. The other parameters used and quantitative values of these parameters in this study are presented in Appendix-1. The absorption spectra corresponding to IRS-P4 OCM wavelengths used for simulation of synthetic data set is also presented in Appendix-1. The details of the underlying assumptions as well as additional details of the computations for this model can be found in Preieur and Sathyendranath, (1981) and Gorden and Morel, (1983). The subsurface irradiance reflectance was converted into normalized water leaving radiance using the following relationship. It is based on work by Gordon et al. (1988) and was modified by Hoge et al. (1995).
\[ [L_w]_N = \frac{(1 - p) s(1 - p) F_0 R}{m^2 Q (1 - r R)} \]  

(5)

Where, \( p \) is the Fresnel reflectance of the sea surface for normal incidence; \( p \) is the Fresnel reflection albedo of the sea surface for irradiance from the sun and sky; \( m \) is the index of refraction of water; \( Q \) is the ratio of upwelling radiance to upwelling radiance toward the zenith; \( r \) is the water-air reflectance for totally diffuse irradiance; \( R \) is the irradiance reflectance just below the sea surface; and \( F_0 \) is the mean extraterrestrial solar irradiance.

4.3 DATA SET FOR ALGORITHM DEVELOPMENT

Using the above described three-component ocean color model, a synthetic data set was generated consisting of 500 reflectance spectra for randomly varying TSM (S), chlorophyll (C) and yellow substance (Y) concentration. To simulate the range of conditions encountered in coastal waters of the Arabian Sea a random number generator was used to provide model input \((C, S, Y)\) assuming a lognormal distribution of these parameters. All the three variables were assumed to be totally uncorrelated to each other, which is typical of coastal waters environment. The input ranges for suspended matter was taken between 3 to 100 mg L\(^{-1}\), for chlorophyll-a 0.05 to 10 mg m\(^{-3}\) and for yellow substance absorption characterized at 440 nm the range for minimum to maximum variations was fixed between 0.05 to 0.35 m\(^{-1}\). These minimum and maximum ranges for all the three variables were selected on the basis of sea truth data collected in the Arabian Sea. The sub-surface irradiance reflectance \( R \) and normalized water leaving radiance
[1-\(n\)] \(N\) were simulated for the first six bands of OCM sensor (i.e. 412, 443, 490, 510, 555 and 670 nm). Two sample results of the simulation are shown in Figure 1, this shows the sub-surface reflectance for increasing concentration of suspended matter (a) in presence of low chlorophyll concentration (i.e. \(C<1.5\) mg m\(^{-3}\)) and (b) in presence of high chlorophyll concentration (i.e. \(C>1.5\) mg m\(^{-3}\)). As evident from the Figure 1, sub-surface reflectance curve peaks at 555 nm for low as well as high chlorophyll concentration is also not very significant as far as reflectance due to suspended matter is concerned.

**4.4 TSM ALGORITHM FOR OCM BANDS**

There are several different approaches to the development of algorithms: the empirical method, the semi-empirical and analytical method (Morel and Gordon, 1980). Using the simulated data set for a typical case II environment, we try to develop a semi-empirical algorithm for the estimation of total suspended matter using IRS-P4 OCM satellite data. Figure 1 shows that for increasing concentration of suspended matter the reflectance peak occurs at 555 nm, even though all six wavelengths appears to be sensitive to suspended matter, but 555 nm and 670 nm are least affected by the presence of other constituents such as chlorophyll-a and yellow substance. The results of the simulated sub-surface reflectance \(R\) in 555 nm and 670 nm are plotted against increasing suspended matter concentration \(S\), in Figure 2(a) and 2(b), respectively. The figures suggest that in both the wavelengths there is a correlation between suspended matter concentration and \(R\). The modeled data indicates more sensitivity of reflectance up to 40 mg L\(^{-1}\) sediment concentration, for increasing concentration of suspended matter reflectance curve starts saturating in both the wavelengths.
Statistical relationship was obtained using the method of least square by fitting an exponential relation between modeled reflectance in 555 nm, 670 nm wavelengths and TSM concentration. The algorithms yielded by least squares fitting were

\[
\log (S) = 17.7* R(\lambda_{555})-0.23 \text{ for } 0.8<S(\text{mg L}^{-1})<80.0 \quad (6)
\]

\[
\log (S) = 13.8* R(\lambda_{670})-0.15 \text{ for } 0.8<S(\text{mg L}^{-1})<80.0 \quad (7)
\]

The coefficient of determination \( (r^2) \) for equation (6) was found to be 0.87, while equation (7) obtained \( r^2 \) value of 0.93 for 500 samples in both the cases. The algorithm derived using reflectance in 670 nm was found more robust compared to algorithm derived using 555 nm wavelengths. Figure 3(a-b) shows the graphical description of these two algorithms. Both of these algorithms are derived using single wavelength therefore they have their own limitations of sensitivity over different ranges of suspended matter concentration. Using simulated data, set, Tassan (1994) has suggested a suspended matter retrieval variable, which makes use of the sensitivity to the variability of the absorption and scattering properties of phytoplankton and suspended matter. Tassan (1994) has used a new variable for the retrieval of the suspended matter concentration \( X_s \), given as

\[
X_s=[R(\lambda_{555})+(\lambda_{670})]*[R(\lambda_{555})/ R(\lambda_{490})] \quad (8)
\]

Where, the first factor, with \( \lambda_{555} \) and \( \lambda_{670} \) in a zone of low chlorophyll sensitivity and yellow substance absorption, is the sensitivity term (essentially because of the high sediment scattering in these wavelengths), where as the second factor, with \( \lambda_{555} \) and \( \lambda_{490} \) is the slope zone of the absorption spectra, and thus depending on \( C \) and \( A_y \) (440), is the compensating term. The variable \( X_s \) was computed and plotted against TSM concentration. A more robust relationship between TSM and remote sensed reflectance
data was obtained, compared to the single wavelength relationship using either \( R(\lambda 555) \) or \( R(\lambda 670) \). Figure 4 shows the relationship between new variable \( X_s \) and TSM concentration. A statistical relationship was developed between \( X_s \) and TSM concentration and the algorithm yielded by the least square fitting was

\[
\log (S) = 7.06^* X_s 0.41 \text{ for } 0.8 < S (\text{mg L}^{-1}) < 80.0 \tag{9}
\]

The coefficient of determination \( r^2 \) for equation (9) was found to be 0.98 for 500 samples. From the statistical relationships shown in equation (6), (7) and (9) it is clear that equation (9) shows a much robust relationships for the estimation of total suspended matter using remote sensing reflectance data.

4.5 TEST OF THE ALGORITHM'S PERFORMANCE

The effectiveness of the retrieval algorithms expressed by equation (6)-(9) was tested on sets of 200 OCM band reflectances, generated by the optical model described in Appendix 1 for random variations of \( C, S \) and \( A_s(440) \). The sets so produced simulate the scatter of data encountered in natural coastal water conditions and allow for an error evaluation in terms of standard deviation.

Figure 5(a-c) shows the scatter plots of TSM retrieval using equation (6), (7) and (9) respectively. Figure 5(a) shows the scatter plot for the TSM estimated using equation (6). This algorithm uses reflectance in 555 nm wavelength. In the case the estimated TSM values were found underestimated for higher concentration of TSM (>40 mg L\(^{-1}\)) and a root mean square (RMS) error of 7.0 mg L\(^{-1}\) was obtained. Figure 5(b) shows the scatter plot for the TSM estimated with the algorithm given by equation (7), using the wavelength 670 nm. An over estimation for TSM concentration greater than 40 mg L\(^{-1}\)
was obtained in this case with an overall RMS error of 4.8 mg L\(^{-1}\). Figure 5 (c) shows the scatter plot for the TSM estimated using equation (9), that is, algorithm using the newly defined variable \(X_s\) (multi-wavelength variable) given by equation (8). Good estimates of retrieved TSM concentration were obtained for this algorithm for the entire range of TSM concentration (0.8 to 80 mg L\(^{-1}\)) with an overall RMS error of 1.22 mg L\(^{-1}\).

The results of the performance test shows that the algorithm using multi-wavelength variable \(X_s\) outperforms the other two that use single channel reflectance, either in 555 nm or 670 nm.

4.6 USE OF TSM ALGORITHM ON OCM IMAGE DATA

IRS-P4 OCM image data of four different dates (7-5-2000, 9-5-2000, 17-11-2000, 27-11-2000) were processed for the estimation of TSM in the Arabian Sea around Mangalore, on west coast of India. The selected images correspond to pre (May data) and post (November data) monsoon periods in this part of the world. After correcting OCM images for the atmospheric path radiance, normalized water leaving radiance were computed in 490, 555 and 670 nm bands, using procedure described by Chauhan et al. (2001). Sub-surface irradiance (R) values were calculated in respective channels using equation (5). The TSM algorithm described by the equation (9) was applied to the atmospherically corrected images for all the four dates. Figure 6(a-b) shows the distribution of TSM concentration in the Arabian Sea at the Mangalore coast for the pre-monsoon season. The sediment flow direction is from north to south in this season. Figure 6 (c-d) shows the distribution is towards south to north in the month of November. The quantitative accuracy of the TSM concentration was also estimated by comparison
with in-situ measurement. A total number of 9 in-situ samples of sediment concentration (synchronous with OCM overpasses) could be correlated with OCM derived TSM concentration. Figure 7 shows a scatter plot of TSM concentration derived using in-situ measurements and OCM satellite data. A good correlation was obtained between in-situ and OCM derived TSM concentration. A root mean square error of 2.5 mg L\(^{-1}\) was obtained for 9 match-up points with a coefficient of determination \((r^2)\), 0.95.

4.7 SUMMARY AND CONCLUSION

Algorithms that use OCM data for the retrieval of total suspended matter (S in mg L\(^{-1}\)) in coastal waters have been established through computations using a three-component model for ocean color. The varying coastal environment has been modeled in terms of a water body characterized by the totally un-correlated optically active constituents of water chlorophyll, total suspended matter and yellow substance. The algorithms using single band and 555 nm and 670 nm reflectance were constructed for TSM estimation, however they were found to give large retrieval errors. A multi-wavelength variable sensitive to the absorption and scattering properties of chlorophyll and suspended matter was then formulated to construct a robust algorithm, which performed well with the simulated data set and also with OCM image data. The algorithm was tested for the west coast of India in the coastal waters of the Arabian Sea near Mangalore. On the whole, the multi-wavelength algorithm appears to yield sufficiently accurate results, even in the presence of rather high chlorophyll and yellow substance values.
SYNOPSIS OF THE FORMULAS

\[ R(\lambda) = 0.33^*B_{s}(\lambda)/A(\lambda) \]
\[ B_{s}(\lambda) = r_{s}B_{s}(\lambda) + r_{b}B_{b}(\lambda) + r_{a}B_{a}(\lambda) \]
\[ B_{s}(\lambda) = B_{s}(550)/(\lambda/550)^{n} \]
\[ B_{b}(\lambda) = 0.12^{*}C^{0.60}a_{b}(550)/a_{b}(\lambda) \]
\[ B_{a}(\lambda) = b_{a}(550)/(\lambda/550)^{n}S \]
\[ A(\lambda) = A_{c}(\lambda) + a_{w}(\lambda)C + a_{b}(\lambda)S + A_{s}(\lambda) \]
\[ A_{c}(\lambda) = A_{c}(440)\exp[-0.0014(\lambda-440)] \]

NOTATION

\[ R \] Subsurface reflectance, i.e., ratio of upwelling to downwelling irradiance just below the sea surface
\[ B_{s} \] Backscattering coefficient (m\(^{-1}\))
\[ A \] Absorption coefficient (m\(^{-1}\))
\[ r \] Backscattering ratio
\[ B \] Volume scattering coefficient (m\(^{-1}\))
\[ b \] Specific volume scattering coefficient (m\(^{-1}\) per unit concentration)
\[ n \] Exponent of wavelength dependence of scattering
\[ a \] Specific absorption coefficient (m\(^{-1}\) per unit concentration)
\[ \lambda \] Wavelength (nm)
\[ C \] Chlorophyll a + phaeophytin a concentration (mg m\(^{-3}\))
\[ S \] Total suspended matter concentration (mg L\(^{-1}\))
\[ A_{c} \] Yellow substance absorption (m\(^{-1}\))
\[ w,c,s,y \] Water, chlorophyll, sediment, and yellow substance (subscripts)

INPUT DATA

Scattering

\[ r_{s} = 0.5 \]
\[ r_{b} = 0.005 \]
\[ r_{a} = 0.015 \]
\[ B_{s}(550) = 0.0020 \text{ m}^{-1} \]
\[ b_{a}(550) = 1 \text{ m}^{-1} \text{ g}^{-1} \]
\[ n_{s} = -4.3 \]
\[ n_{b} = -1 \]

Absorption

\[ A_{c}(440) = 0.015 \text{ m}^{-1} \]
\[ a_{w}(443) = 0.07 \text{ m}^{2} \text{ mg}^{-1} \quad \text{if } C \leq 1 \text{ mg m}^{-3} \]
\[ a_{w}(443) = 0.018 \text{ m}^{2} \text{ mg}^{-1} \quad \text{if } C \geq 1 \text{ mg m}^{-3} \]
\[ a_{c}(443) = 0.034 \text{ m}^{2} \text{ g}^{-1} \]

Absorption spectra (relative units):

<table>
<thead>
<tr>
<th>Wavelength (nm)</th>
<th>412</th>
<th>443</th>
<th>490</th>
<th>510</th>
<th>555</th>
<th>670</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A_{c} )</td>
<td>1.13</td>
<td>1.33</td>
<td>3.20</td>
<td>5.05</td>
<td>28</td>
<td></td>
</tr>
<tr>
<td>( a_{w} )</td>
<td>0.88</td>
<td>0.75</td>
<td>0.53</td>
<td>0.27</td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td>( a_{c} )</td>
<td>1.35</td>
<td>0.75</td>
<td>0.65</td>
<td>0.27</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td>( A_{c} )</td>
<td>1.54</td>
<td>0.52</td>
<td>0.39</td>
<td>0.21</td>
<td>0.042</td>
<td></td>
</tr>
</tbody>
</table>
Fig. 1 Simulated sub-surface reflectance R for increasing TSM concentration
(a) in the presence of chlorophyll <1.5 mg/m³
(b) in the presence of chlorophyll > 1.5 mg/m³
Fig. 2 (a) Relationship between total suspended matter (TSM) and reflectance in 555 nm band, (b) relationship between TSM concentration and reflectance in 670 nm band.