

# Assessment of Some Water Quality Parameters Using MODIS Data along the Red Sea Coast, Egypt

AYMAN H. NASR, BELAL M. EL LEITHY and ASHRAF K. HELMY  
National Authority for Remote Sensing and Space Sciences  
23 Joseph Broz Tito st., El-Nozha El-Gedida, Cairo  
EGYPT  
aymanasr@hotmail.com

**Abstract:** - The Red Sea coastal area is characterized by a wealth of natural heritage and resources that present an attractive element for tourism. It is considered one of Egypt's important sectors for sustainable development. At present, this area witnesses an extensive and diverse activities such as; tourism, industry, harbors and fisheries. These anthropogenic activities may significantly impact the sea water quality. In this paper we estimated some water quality parameters in the surface water of the Egyptian sector of the Red Sea by processing MODIS satellite data using SeaDas software. These parameters include: Chlorophyll a concentration (Chl-a), Total Suspended Matter (TSM), and Sea Surface Temperature (SST). A field trip was conducted and several samples were collected representing different coastal water environments for validation and verification. A comparison between the derived estimates and the concurrent bio-optical in situ measurements of the same locations were performed and produced correlative results. Although the retrieved and measured Chl-a and SST are well correlated, the TSM needed an offset for reasonable correspondence. Therefore, the obtained results confirm that the enhanced sensitivity and coverage of MODIS data can provide a significant tool for accurate assessment of water quality parameters.

**Key-Words:** - Water quality parameters, MODIS data, Red Sea coast, Bio-optical measurements

## 1 Introduction

The Red Sea coastal waters are subject to considerable ecological pressure as a result of domestic and industrial pollution discharges. Consequently, water quality adjacent to utilized areas should be periodically monitored. Attention was focused on the Egyptian sector of the Red Sea delimited geographically by latitudes 23° 00' N and 30° 00' N and longitudes 32° 20' E and 36° 40' E approximately, as shown in Fig. 1. To fully benefit from remote sensing data in oceanographic assessment, it is necessary to use the data in synergy with models through data assimilation methods. The conventional measurement of water quality parameters requires in situ sampling, analysis, and measurements done in laboratories. These techniques are expensive and time consuming. Ocean satellites offer rapid, concurrent and synoptic observations which can be routinely acquired to derive surface water quality parameters that cover much of the coastal environment. These parameters are the primary factor affecting ecological processes and serve as indicators of ecosystem health.

Visible radiation is the only portion of the electromagnetic spectrum that appreciably penetrates into the water column. This capability permits the retrieval of particulate and dissolved substance

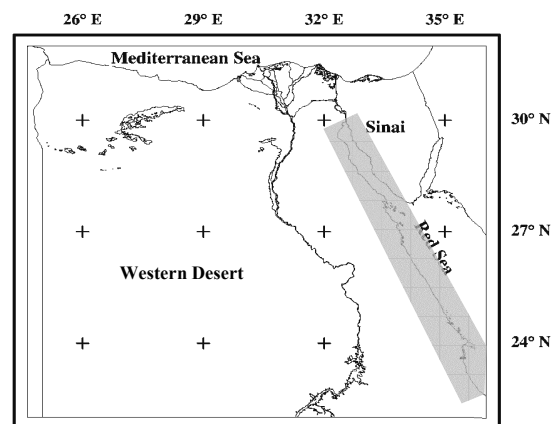


Fig.1. Location map of the study area

concentrations and inherent optical properties within the ocean's surface layer. Infrared (IR) wavelengths are well suited for sea surface temperature from satellites because the earth's thermal emission peaks in the (IR) spectrum and the emissivity of water in the IR is very close to unity. The basic idea of remote sensing of water quality is to use the differences in spectral reflectance. These 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. Consequently, these observed spectral radiances could be decomposed and measurement of the major water quality parameters (e.g., Chl-a, TSM, and SST) could be quantified [1] after correction of the sensor signal for atmospheric absorption and scattering of the gases and aerosols.

The Chl-a concentration provides a measure of phytoplankton abundance and biomass [2]. It is a key input to the primary ocean production product and a good trace of oceanographic currents, jets, and plumes. The TSM is one of the most important oceanographic parameters. It is responsible for visible changes in surface waters. It is used in the analysis of complex bio-optical properties of coastal and estuarine regions. The global distribution and variability of the SST are key inputs to earth energy, hydrological balance, and long-term climate change studies. Therefore, the main purpose of this study is to employ the modern applications of remote sensing observations on calculation and retrieval of these geophysical water quality parameters, since it was not used so far in the study area to the best of the author's knowledge.

## 2 Materials and Methods

Satellite observations of ocean color began in 26 June 1978 with the first purpose-built oceanographic satellite, Seasat 1. Since then, a wide range of remote sensing satellites are designed and launched to improve the monitoring process of water characteristics. Their sensors require a set of narrow, sensitive spectral channels, to remove atmospheric effects and resolve the spectral signals used to estimate water constituents [3]. Awareness of the capabilities and limitations of the various systems is the first step in selecting an appropriate satellite to meet the needs of a specific application. Therefore, in this study we used the Moderate Resolution Imaging Spectrometer (MODIS) launched on AQUA in May 2002. It is a passive, imaging spectro-radiometer with 36 spectral bands that cover the visible and infrared spectrum. The study area is covered by one MODIS satellite scene acquired on 24 July 2006, as shown in Fig. 2.

Two general steps are required to obtain quantitative estimates of various water constituents from calibrated radiances measured by MODIS



Fig.2. MODIS satellite scene of the study area

satellite sensor. The first is removal of the effect of the atmosphere (atmospheric correction). The second is the derivation of water quality parameters based on water-leaving radiance or surface reflectance estimates [4]. In oceanic waters, with knowledge of the spectral characteristics of their constituents, reflectance models and ocean color algorithms have been developed for estimating seawater constituents from remote sensing [5]. Bio-optical studies in various coastal waters have demonstrated the need for empirical [6] and semi-analytic [7, 8] algorithms in order to obtain better estimates of various in-water constituents. The empirical algorithms provide direct relationships between ratios of remote sensing reflectance or water leaving radiances and seawater constituents such as Chl-a.

The SeaDAS (SeaWiFS Data Analysis System) version 5.0.5 software was used to read, process, and display the MODIS data files. This data was subjected to multi steps processes and the used algorithms provided a reasonable means to derive sequences of water quality concentration maps of coastal waters. The OC4 algorithm [9] was used, which is a four-band maximum band ratio formulation, to estimate Chl-a concentration from atmospherically corrected satellite reflectance signals, as shown in Fig. 3. Similar empirical algorithm [1] has also been used for mapping TSM distribution, as illustrated in Fig. 4, and finally [10] algorithm was implemented to depict the MODIS SST, as shown in Fig. 5.

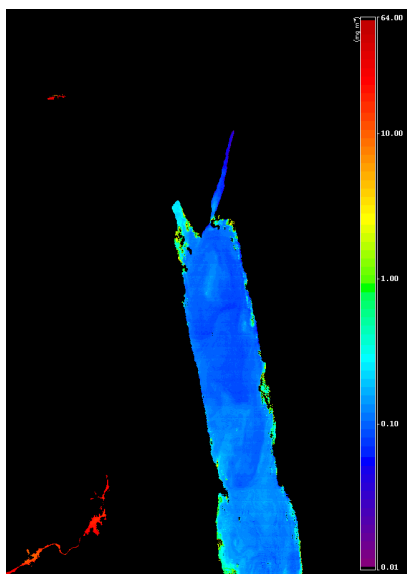


Fig.3. Chlorophyll-a concentration

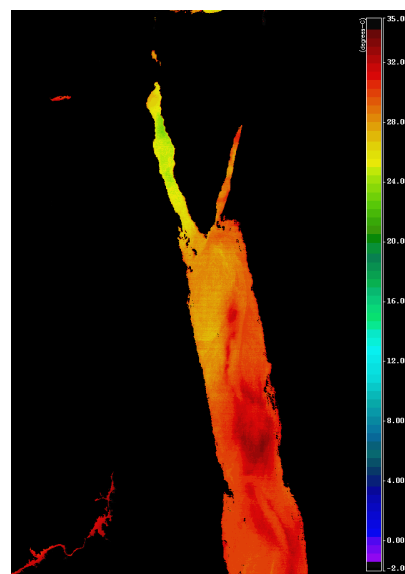


Fig.5. Sea surface temperature distribution

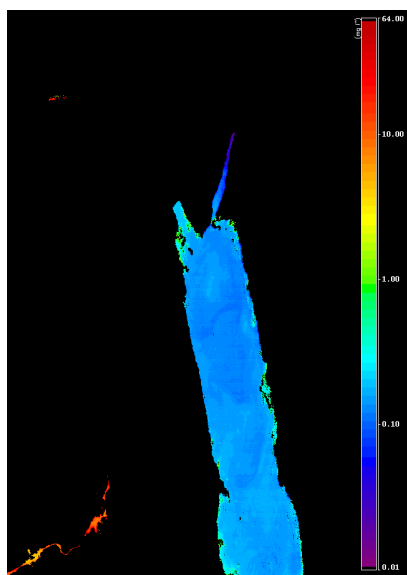


Fig.4. Suspended matter concentration

representing different coastal water environments, as shown in Fig. 6. These samples have been laboratory analyzed (at the National Institute for Oceanography and Fishery) for measuring different water quality parameters (Chl-a and TSM). Additional data were also recorded during this field survey such as the exact geographic location using (GPS) and the Sea Surface Temperature (SST).



Fig.6. The base map of the collected water samples sites.

Maximum benefits will be achieved when satellite data are paired with concurrent field data. A limited number of in situ measurements can provide the ground verification and validation information needed to extrapolate spatially over a coastal environment using synoptic MODIS imagery [11]. Therefore, a field trip was conducted along the coastal area of the Red Sea during the period of the satellite pass (July 2006) for better correlation with optical measurements. It resulted in acquisition of 8 geographically selected discrete water samples

### 3 Results and Discussions

Tables 1, 2 represent the water quality parameters values derived from MODIS and the in situ measurements of the 8 locations of the field trip respectively. After exploring the individual results, the range and the form vary per parameter. For the first parameter (Chl-a) to verify and validate the implementation and to see if it performs well, a comparison between the in situ measurements and the MODIS derived values was carried out and depicted in figure 7. One can see a reasonable agreement between them with no significant differences. However, the MODIS derived values are a little bit underestimated with a Root Mean Square Error (RMSE = 0.13). It should be noted that the Chl-a MODIS derived value of the first location site is slightly higher than the in situ measured one. This result suggests that Chl-a value tend to increase with the effect of bottom reflectance which contributes to the water-leaving radiance in this area.

Table 1: MODIS derived values at the 8 locations of the field trip

Site No.	Lat.	Long.	Chl-a mg m <sup>-3</sup>	TSM mg/l	(SST) C °
1	27° 11'	33° 50'	0.54	0.39	28.33
2	26° 47'	33° 56'	0.32	0.24	28.60
3	26° 30'	34° 00'	0.09	0.14	28.69
4	26° 15'	34° 12'	0.09	0.15	28.80
5	26° 12'	34° 13'	0.08	0.14	28.90
6	26° 08'	34° 14'	0.13	0.15	29.92
7	25° 04'	34° 45'	0.15	0.13	30.30
8	23° 09'	35° 36'	0.16	0.22	33.00

Table 2: The in situ measurements values of the 8 samples

Sites No.	Lat.	Long.	Chl-a mg m <sup>-3</sup>	TSM mg/l	(SST) C °
1	27° 11'	33° 50'	0.40	9.16	28.6
2	26° 47'	33° 56'	0.39	9.13	28.6
3	26° 30'	34° 00'	0.23	8.28	29.1
4	26° 15'	34° 12'	0.29	9.45	29.1
5	26° 12'	34° 13'	0.17	12.11	29.3
6	26° 08'	34° 14'	0.22	10.97	29.5
7	25° 04'	34° 45'	0.28	8.33	29.9
8	23° 09'	35° 36'	0.29	13.09	33.4

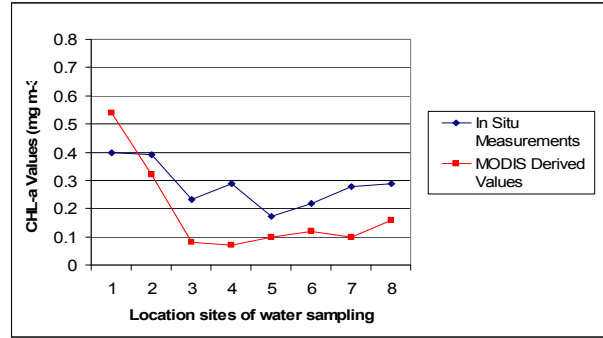


Fig.7. Relationship between MODIS derived Chl-a and the in situ measurements values

For the second parameter (TSM), Fig. 8 shows that the range of the MODIS TSM distributions is underestimated (0.13 to 0.39 mg l<sup>-1</sup>). From the figure, although the in situ measured values are relatively higher than the retrieved MODIS ones and apart from the two irregularities at sites 5-8, after correction with a calibration value (an offset = 9.5 mg l<sup>-1</sup>), Fig. 9 shows a better correlation between them overall (RMSE = 4.86). The calibration value ( $\epsilon$ ) is calculated for minimum RMS error using the following equation:

$$\text{RMS (E)} = \text{Square Root} \left\{ \frac{\sum (TD - Tm + \epsilon)^2}{N} \right\}$$

Where, TD is the derived value,  
Tm is the measured value  
 $\epsilon$  is the calibration value, and  
N is the number of samples

For calculating  $\epsilon$ , the equation  $(dE/d\epsilon) = 0$  is solved.

It should be kept in mind that the data in this study was obtained in limited field samples and contain more spatial variations as a result of being compared to the increased resolution of the MODIS data (1.1 km). Also, the used empirical algorithm may need to be optimized for regional coastal waters to obtain better estimates of TSM concentrations.

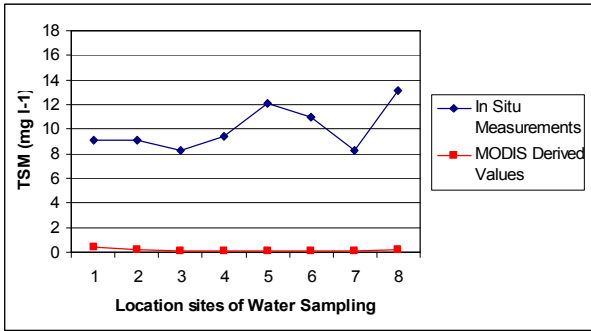


Fig.8. Relationship between TSM retrieved from MODIS and the in situ measurements values

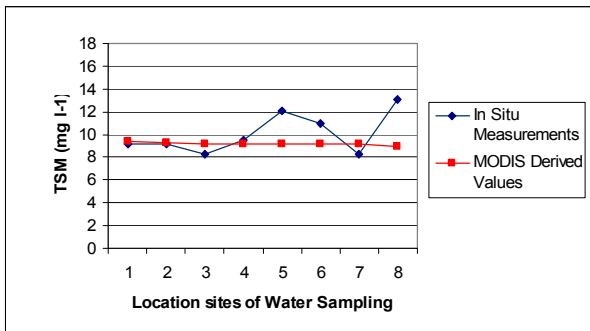


Fig.9. The TSM relationship after the correction with an offset

For the last parameter (SST), Fig. 10 depicts a very well correlation and almost identical pattern between them. The accuracy of derived SST assessed by comparing them against in situ measurements is less than 0.5°C and the RMSE value is found to be 0.37.

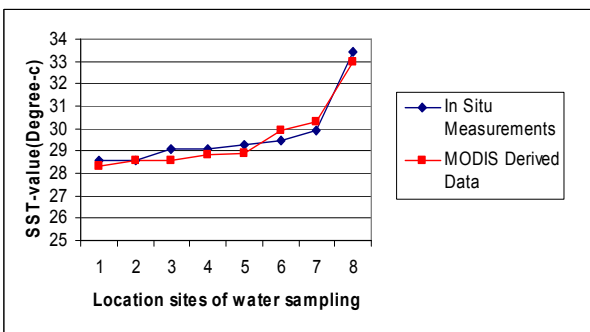


Fig.10. Comparison between MODIS derived SST versus the in situ measurements values

Fig. 11 represents the RMSE values of the three studied water quality parameters. The chart reveals that the Chl-a estimates are the closer ones (i.e., they have the best, minimum, RMSE values), secondly are the SST, then the TSM values to

produce a satisfactory correspondence. Consequently, these results verify the applicability of the MODIS data and prove its mathematical models excellent performance in calculation and retrieval of geophysical water quality parameters

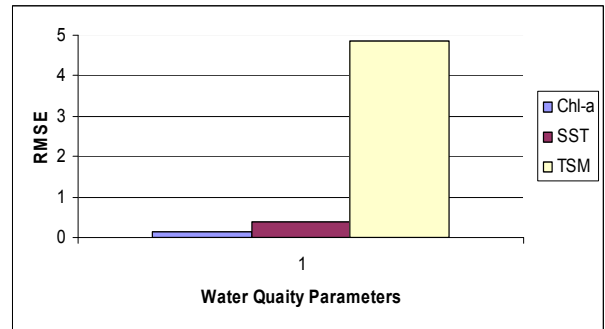


Fig.11. RMSE values of the different water quality parameters

#### 4 Conclusions

Ocean satellites can offer rapid, concurrent and synoptic observation to derive seawater constituents. In this study MODIS satellite data and various mathematical algorithms were used. Distribution, concentration, and dispersal maps of different water quality parameters (Chl-a, TSM, and SST) have been generated. The results were validated by using concurrent data sets of 8 different in situ field measurements acquired on July 2006. Comparisons were carried out and showed that for the Chl-a and the SST distributions the relationship between the derived and the measured ones are very well correlated (RMSE= 0.13 and 0.37) respectively, While the concentration of TSM needed an offset for satisfactory correspondence (RMSE= 4.86).

The capability in applying concurrent MODIS data and minimized in situ measurements are the main advantages of using bio-optical mathematical models in calculation and retrieval of geophysical water quality parameters. Moreover, the enhanced sensitivity and coverage of the MODIS sensors provides a number of significant improvements and excellent pathway to prepare for future sensors (e.g., the Visible/Infrared Imager/Radiometer Suite (VIIRS)). New generations of geostationary, hyperspectral, and high-resolution satellite sensors will allow for longer data collection. Along with the improvements in the atmospheric correction algorithms and the quality of the sensors received signal, better and accurate estimates of water quality parameters can be obtained.

## Acknowledgements

The authors are grateful to the National Authority for Remote Sensing and Space Sciences (NARSS) for supporting this study.

## References

- [1] Clark, D.K., *MODIS Algorithm Theoretical Basis Document (ATBD 18) Bio-Optical Algorithms Case 1 Waters*, Version 1.2, 1997, [http://modis.gsfc.nasa.gov/data/atpd\\_mod18.pdf](http://modis.gsfc.nasa.gov/data/atpd_mod18.pdf)
- [2] Martin, S., *An Introduction to Ocean Remote Sensing*, Cambridge University Press, ISBN 0521-802806. 426 P, 2004.
- [3] Brown, C.W., Connor, L.N., Lillibridge, J.L., Nalli, N.R., and Legeckis, R.V., An Introduction to Satellite Sensors, Observations and Techniques, R.L. Miller et al. (eds.), *Remote Sensing of Coastal Aquatic Environments*, pp. 21-50, Springer, Printed in the Netherlands, 2005
- [4] Muller-Karger, F.E., Hu, C., Andrefouet, S., Varela, R., and Thunell, R., The Color of the Coastal Ocean and Applications in the Solution of Research and Management Problems. R.L. Miller et al. (eds.), *Remote Sensing of Coastal Aquatic Environments*, pp. 101-127, Springer, Printed in the Netherlands, 2005. O'Reilly,
- [5] Carder, K.L., Chen, F.R., Lee, Z.P., Hawes, S.K. and Kamykowski, D., Semianalytic Moderate-Resolution Imaging Spectrometer Algorithms for Chlorophyll a and Absorption with Bio-Optical Domains Based on Nitrate Depletion Temperatures, *J. Geophys. Res.*, Vol. 104, 1999, pp. 5403-5421.
- [6] D'Sa, E.J., Hu, C., Muller-Karger, F.E, and Carder, K.L., Estimation of Colored Dissolved Organic Matter and Salinity Fields in Case 2 Waters Using SeaWiFS: Examples from Florida Bay and Florida Shelf, *Proc. Indian Acad. Sci. (Earth and Planetary Sci.)* Issue 111, No. 3, 2002, pp. 197-207.
- [7] Reynolds, R.A., Stramski, D., and Mitchell, B.G., A Chlorophyll-Dependent Semianalytical Reflectance Model Derived from Field Measurements of Absorption and Backscattering coefficients within the Southern Ocean, *J. Geophys. Res.* Vol. 106 (C4), 2001, pp. 7125-7138.
- [8] Maritorena, S., Siegel, D.A., and Peterson, A.R., Optimization of a Semianalytical Ocean Color Model for Global-Scale Applications, *Applied Optics*, Vol. 41, No. 15, 2002, pp 2705-2714.
- [9] O'Reilly, J.E., Maritorena, S., Siegel, D.A., O'Brien, M.C., Toole, D., Chavez, F.P., Strutton, P., Cota, G.F., Hooker, S.B., McClain, C.R., Carder, K.L., Müller-Karger, F., Harding, L., Magnuson, A., Phinney, D., Moore, G.F., Aiken, J., Arrigo, K.R., Letelier, R., & Culver, M., Ocean Color chlorophyll algorithms for SeaWiFS, OC2, and OC4: Version 4, In S.B. Hooker & E.R. Firestone (Eds.), *SeaWiFS Post launch Calibration and Validation Analyses, Part 3*, NASA Technical Memorandum, 2000-206892, vol.11, 2000, pp. 9–23. Greenbelt, MD: NASA Goddard Space Flight Center.
- [10] Brown, O.B. and Minnett, P.J., *MODIS Infrared Sea Surface Temperature Algorithm-Algorithm Theoretical Basis Document, Products: MOD28*. ATBD Reference Number: ATBD-MOD-25, 1999.
- [11] Miller, R.L., Del Castillo, C.E., and McKee, B.A., *Remote Sensing of Coastal Aquatic Environments – Technologies, Techniques and Applications*, Published by Springer, ISBN 1-4020-3099-1, P.O. Box 17, 3300AA Dordrecht, The Netherlands, 2005.