The estimation of total suspended matter from satellite imagery of tropical coastal water Berau Estuary, Indonesia

W Ambarwulan¹, M S Salama², W Verhoef² and C. M. Mannaerts²

¹ Geospatial Information Agency, Indonesia
² Twente University, The Netherlands

E-mail: wiwin.ambarwulan@big.go.id, w_ambarwulan@yahoo.com

Abstract. Water in coastal and estuary areas needs to be investigated as human activities is allegedly decrease their quality. This has led to optical remote sensing for mapping optical water quality using empirical and semi-analytical approaches. Therefore, this study aims to estimate the Total Suspended Matter (TSM) concentration from Medium Resolution Imaging Spectrometer (MERIS) data using a spectral unmixing approach combined with a radiative transfer model. This approach was implemented in the equatorial tropical coastal water, the Berau estuary, Indonesia, by generating a look-up table (LUT) of top-of-atmosphere radiance spectra through the coupled forward models, and the endmembers were selected from the LUT. The spectral unmixing algorithm was employed to the MERIS data for decomposing the image into haze and sediment components. The data were then transformed into images of a constant haze level corresponding to 50 km visibility, and the atmospheric correction was applied. Furthermore, the TMS concentration was retrieved using the inverse semi-analytical Kubelka-Munk model. The result gave overestimated TSM concentration values on clear waters. However, in turbid waters, a lower RMSE was obtained, and the coefficient of determination was higher than in clear waters.

1. Introduction
Remote sensing (RS) is an instrument for mapping and monitoring the dynamics of coastal waters at various levels of scale, namely local, regional and global [1]. The RS has been used to map optical water quality such as concentration of total suspended sediment (TSM), chlorophyll-α, and gelbstoff absorption by using empirical/statistical and semi-analytical approaches [2]. The empirical approach is a simple method that correlates between TSM concentration measured and RS reflectance based on band ratio [3, 4]. This approach is not widely appropriate in coastal water due to gelbstoff and minerals from the freshwater plume, which significantly impacting the optical properties [5]. Previous studies have used a semi-analytical approach such as a bio-optical model for estimating TSM concentration [6, 7], chlorophyll-α concentration [8, 9], and yellow substance or gelbstoff absorption [10]. Medium Resolution Imaging Spectrometers (MERIS) have also been used to monitor TSM concentrations using a semi-analytic approach [11]. Meanwhile, the study of water quality in Case-2 waters was disturbed due to heterogeneity, river discharge, tides, resuspension of bottom sediment [12], and failure of most of the atmospheric correction methods [13]. The coastal waters from satellite imagery consist of several materials mixed in one pixel, such as clear water, suspended sediments, phytoplankton, and others [14]. Therefore, spectral unmixing techniques are used to solve the mixed pixel problem [1].
In tropical water such as Indonesian waters, the study of a semi-analytical approach was limited. The mapping of TSM concentration from MERIS data has been carried out in Berau Estuary using different standard Artificial Neural Network (ANN) processor algorithms [16]. Furthermore, the TSM estimation on tropical water accuracy was relatively low because the semi-analytical models were developed on coastal waters in temperate regions such as European waters. In the equatorial tropical waters, highly variable atmospheric conditions have made water quality mapping less accurate. Therefore, for a better understanding of the bio-optical model than the Specific Inherent Optical Property (SIOP) of Berau estuary, the estimation was carried out using RS data and in situ measurement [15], rather than standard ANN to increase the accuracy. Meanwhile, the TSM concentration of Berau estuary has been estimated using the semi-analytical approach based on the Kubelka-Munk (K-M) model to improve the accuracy [16]. It has also been discovered that Band 6 (620 nm) was the most appropriate band for estimating TSM concentration [16]. Similarly, a study has been conducted at turbid Yangtze estuary from MERIS using a semi-empirical radiative transfer (SERT) model [11].

In satellite data, the spectral signal from a pixel generally shows a combination of various spectral signals known as a mixed pixel. Several approaches, such as spectral unmixing [18] and Bayesian unmixing models [19], were established to overcome this challenge. However, spectral unmixing is the most widespread method to decompose a mixed pixel into endmembers and abundances [20, 21] and has been successfully used for flood [22] and coral reef mapping [23]. Furthermore, it was also applied for retrieving suspended sediment concentration from MERIS data [24, 25, 14]. Meanwhile, its successful application for mapping water quality in subtropical waters has become the basis for consideration in this study, namely the methodology development for mapping TSM concentrations in equatorial tropical waters. Therefore, this study aims to estimate TSM concentration from MERIS imagery using a spectral unmixing approach combined with a radiative transfer model.

2. Material and methods

2.1. Study Area
The Berau estuary is a complex and dynamic coastal water in Berau Regency, East Kalimantan, Indonesia (Figure 1). The estuary is among the four Marine Protected Area (MPA) in Indonesia and is popularly known as the richest marine biodiversity in the world. Furthermore, the upper part of the estuary is dominated by oil plantations which were previously tropical forests. However, the conversion of tropical forests into oil palm has led to land degradation and decreased water quality.

Figure 1. Location of the study area, the Berau estuary

2.2. Samples and remote sensing reflectance collection
The field survey was conducted in the study area during the dry season, from August 27 to September 18, 2007. The in-situ data were collected at the depth near the shelf edge and open-ocean from 100 m to
the turbid coastal water less than 2 m depth. Furthermore, water spectra, both the total downwelling and upwelling radiance, were measured between 09:00 and 15:00 Local Time (Central Indonesian Time) with an Ocean optic Spectrometer USB4000. These spectra were measured at three different water depths, namely 10, 30, and 50 cm. Similarly, some measurements of spectral characteristics such as sky irradiance, and water-leaving reflectance were conducted. Furthermore, the subsurface irradiance reflectance \( R_{\omega} \) was calculated by considering parameters such as subsurface irradiance, sky irradiance, and water-leaving radiance. The parameter of inherent optical properties (IOPs) such as TSM and Chlorophyll-a concentration was analyzed from water samples collected at a depth of 50 cm under the water surface.

2.3. Ocean Color Data

In this study, the MERIS data on August 31, 2007, were used. Meanwhile, the MERIS that crossed the study area was around 10:00 local time or 02:00 Universal Coordinated Time (UTC). Field measurements were carried out at an interval of one to five hours with the MERIS overpass. From 18 field observations, only one day of the field campaign was a match-up with cloud-free MERIS products (table 1).

| Recorded Time          | Field stations | MERIS Imagery                        |
|------------------------|----------------|--------------------------------------|
| August 27 to August 30 | 35             | Poor due to clouds cover and sunglint |
| 2007                   |                |                                      |
| August 31, 2007        | 9              | Good quality, less cloud and sunglint |
| September 01 to September 18, 2007 | 127           | Flawed due to clouds cover and sunglint |

2.4. Method

The spatial differences of the top-of-atmosphere radiance \( L_{TOA} \) signal of coastal waters are mixed pixels that can be divided into the atmospheric haze and suspended sediment [24]. These components have a different spectral signature and are separated by the spectral unmixing technique. Estimating TSM concentration was used as an integrated approach based on the radiative transfer model within the atmosphere system by applying a spectral unmixing technique (Figure 2).

![Figure 2. Research Flowchart](image-url)
2.4.1. Establishing a look-up table (LUT) of TOA radiance simulations.
The LUT of $L_{\text{TOA}}$ was developed by simulating the combinations of four visibility levels, namely 10, 20, 40, and 50 km, and nine TSM concentration levels, namely 1, 5, 8, 10, 30, 50, 60, 80, and 100 mgl$^{-1}$. The remote sensing reflectance ($R_{\text{rs}}$) simulation was established from TSM concentration using a K-M model. Subsequently, the relationship between $R_{\text{rs}}$ and TSM concentration [14, 9] was computed based on equation 1:

$$R_{\text{rs}} = \frac{\alpha \beta C_{\text{TSM}}}{1 + \beta C_{\text{TSM}} + \sqrt{1 + 2 \beta C_{\text{TSM}}}}$$  \(1\)

Where $C_{\text{TSM}}$ was the TSM concentration, and $\alpha$ and $\beta$ are fitting coefficients, established by correlating the TSM model to TSM in situ. The fitting coefficients value obtained is shown in Table 2. The $R_{\text{rs}}$ was further converted into the water leaving reflectance ($r$) by applying equation $r = \pi \times R_{\text{rs}}$. Finally, establish the $L_{\text{TOA}}$ (W m$^{-2}$ sr$^{-1}$ μm$^{-1}$) of the MERIS using equation 2:

$$L_{\text{TOA}} = L_0 + \frac{G+r}{1-r+A}$$  \(2\)

where $L_0$ is $L_{\text{TOA}}$ for zero surface albedo, $A$ is the spherical albedo of the atmosphere, and $G$ is the gain factor for the target and the background. The constants $L_0$, $A$, and $G$ were from MODerate spectral resolution atmospheric TRANsmittance (MODTRAN). In this study, parameters inputs for MODTRAN were Lambertian surface reflectance waters, a rural aerosol model, a homogeneous atmosphere, and surface albedos in 0%, 50%, and 100%. Table 2 displays the MODTRAN output parameters (on selected wavelength and visibility) for August 31, 2007.

| Visibility (km) | 560 nm | 620 nm | 660 nm |
|---------------|--------|--------|--------|
| L0 40         | 24.1   | 15.6   | 11.9   |
| 50            | 23.0   | 14.7   | 11.1   |
| A 40          | 0.120  | 0.096  | 0.081  |
| 50            | 0.113  | 0.090  | 0.075  |
| G 40          | 387    | 363    | 339    |
| 50            | 392    | 367    | 343    |
| $\alpha$      | 0.061  | 0.097  | 0.084  |
| $\beta$       | 0.039  | 0.012  | 0.014  |

2.4.2. Selection of endmembers.
In this study, the endmember was selected from a LUT, calculated based on a radiative transfer model. The basis selection of endmembers was spectra of $L_{\text{TOA}}$ created from the combination of haze and sediment. The Spectral $L_{\text{TOA}}$ that correlates to the minimum haze level and sediment levels was considered as the darkest pixel in the ocean part. Meanwhile, the algorithms of the linear unmixing approach were applied as described in [1, 24].

2.4.3. Implementing the spectral unmixing algorithm to the MERIS imagery.
The MERIS was processed through three main steps, namely (1) establishing a MERIS image by applying the spectral unmixing, (2) calculating the MERIS remote sensing reflectance by applying MODTRAN, and (3) applying the semi-analytical approach, K-M model to derive TSM concentration from the MERIS reflectance.

3. Results and discussions

3.1. Spectral Shape of TOA radiance simulations
The spectra of $L_{\text{TOA}}$ simulations were established using Equations 1 and 2 with 36 combined input of visibility atmosphere and TSM concentration. The $L_{\text{TOA}}$ spectrum for all 36 haze and sediment combinations is shown in Figure 3, which indicates a significant increase in the TSM concentrations due to a change in the spectral shape of $L_{\text{TOA}}$. At low TSM concentrations (1 to 10 mgl$^{-1}$), the spectral
shape was low, corresponding to clear water. Furthermore, by increasing the TSM concentration from 30 to 100 mg l\(^{-1}\), the spectra shape resembles turbid waters. Based on transforming 36 spectra as shown in Figure 4, the sediment effects were maintained, while haze variations were removed.

In this study, spectral unmixing was successfully separated sediment and haze, especially at visibility of 50 km. This is in line with [23], which stated that spectral unmixing proved successful for the water classification.

**Figure 3.** Simulated \(E_{\text{TOA}}\) for 36 combinations of four haze visibility levels and nine-level of TSM concentrations (before applied spectral unmixing technique)

**Figure 4.** The \(E_{\text{TOA}}\) simulation for 36 combinations of visibility and TSM concentrations (after applied spectral unmixing technique)
3.2. **Spectral Shape of LTOA MERIS images**

The MERIS of Berau estuary recorded August 31, 2007, has heavy haze variations and sediment components from the adjacent coasts effect. Therefore, the pixel of imagery was mixed. The haze component of all MERIS bands was removed using the projection method of spectral unmixing technique. At the same time, K-M model was applied for deriving TSM concentration from MERIS surface reflectance. From the previous result [15], MERIS of wavelength 620 nm (band 6) was the most suitable to retrieve the TSM concentration in Berau estuary waters. The distribution of TSM concentration, as shown in Figure 5, was high at the estuary and descended towards the sea.

![Figure 5](image)

**Figure 5.** The TSM concentration distribution map derived from the MERIS image on August 31, 2007

The coefficient of determination ($R^2$) and the root mean square error (RMSE) was established to analyze the relationship between TSM in situ and estimated value from MERIS data (Figure 6). The two sets of field data measurements were used to validate the TSM derived. The first data set collected from August 31, 2007, corresponded with MERIS and most data in the medium clear water. Meanwhile, the second data set collected on August 29, 2007, was one day before MERIS data and distributed in turbid water. Figure 6a showed that the higher correlation between TSM derived and in situ was discovered in turbid water on August 29, 2007 ($R^2 = 0.96$). Although the TSM derived in turbid water seems more encouraging as the values were around the 1:1 line, it was overvalued in the clear water (Figure 6b).

![Figure 6](image)

**Figure 6.** Scatter plot between TSM derived from MERIS and TSM in situ measured August 29, 2007, in relatively turbid water (a) and in clear water measured on August 31, 2007 (b)

This study discovered that the atmospheric correction and inverse K-M model increased the accuracy of TSM concentration derived from MERIS data. Furthermore, the $R^2 (0.96)$ was higher in turbid water.
than in clear water, and the proposed method gave a better accuracy result compared to the TSM derived using empirical approach ($R^2=0.75$) [14]. Diversities between TSM measured, and TSM derived from MERIS data were due to (i) clouds cover, (ii) increasing mixed pixel, (iii) reflectance effect from coral reefs and islands around the estuary, and (iv) the presence of the tidal flats. This is in line with [26], which stated that clouds and shadows caused a decrease in the reflectance accuracy. In the clear water, the TSM derived was overvalued compared to TSM concentration *in situ* because the wavelength of 620 nm was significantly influenced by sediment [27]. These results were similar to a study by [24] which discovered that the wavelengths (560 or 620 nm) were appropriated for TSM retrieval.

4. Conclusions

The spectral unmixing technique with the semi-analytical radiative transfer model and MODTRAN atmospheric correction provided a robust algorithm for estimating TSM concentrations from satellite imagery in tropical coastal waters. The results showed that the model proposed it improved the accuracy of TSM concentration mapping compared to the empirical and standard ANN approaches. A simple atmospheric correction procedure with standard visibility of 50 km can be applied for MERIS images assuming a homogenous atmosphere. In turbid waters, the model was more robust than in clear areas, which was indicated by a high $R^2$ value and a lower RMSE.

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