

STUDY OF ESTIMATE CONCENTRATION OF WATER CONSTITUENTS AT BADUNG STRAIT BALI USING INVERSE MODEL

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ABSTRACT

An algorithm was employed to retrieve the concentrations of three water constituents, chlorophyll-a, suspended matter and colored dissolved organic matter (CDOM) from MODIS (Moderate-Resolution Imaging Spectrometer) in wide range covering from oligotrophic case-1 to turbid case-2 waters at the Badung Strait Bali. The algorithm is a neural network (NN) which is used to parameterize the inverse of a radiative transfer model. It's used in this study as a multiple nonlinear regression technique. The NN is a feed forward back propagation model with two hidden layers. The NN was trained with computed radiance covering the range of chlorophyll-a from 0.001 to 64.0 $\mu\text{g/l}$, inorganic suspended matter from 0.01 to 50.0 mg/l , and CDOM absorption at 440nm from 0.001 to 5.0 m^{-1} . Inputs to the NN are the radiance of the five spectral channels which were under discussion for MODIS. The outputs are the three water constituent concentrations. The NN algorithm was tested using in-situ data set on May, September, November 2005 at the Badung Strait Bali and the north sea of Sumbawa Island and applied to MODIS. The coefficient of determination (R^2) between chlorophyll-a concentrations derived from simulation and in-situ data is 0.327, for suspended matter R^2 is 0.408. No in-situ measurements of CDOM available for validation. Also, in-situ data were compared with the corresponding distribution obtained by the NASA standard OC4 (OC3M) for MODIS chlorophyll-a algorithm and giving R^2 0.188. This study gives better accuracy compare with standard algorithm. How ever both studies are giving over estimate chlorophyll-a concentration. Since there are no standard MODIS products available for suspended matter and CDOM, the result of the retrieval by the NN for these two variables could only be assessed by a general knowledge of their concentrations and distribution patterns

Keywords: Inverse Model, Neural Network, Ocean Color Algorithm, Chlorophyll-a, Suspended Matter, CDOM, MODIS

ABSTRAK

Telah dilakukan algoritma untuk mendapatkan konsentrasi materi pokok air laut yaitu, kloropil-a, materi tersuspensi anorganik dan materi organik terlarut berwarna (CDOM) dari satelit MODIS (*Moderate-Resolution Imaging Spectrometer*) pada area yang luas, dari daerah *oligotrophic (case-1)* s/d daerah air keruh (*case-2*) di Selat Badung Bali. Algoritma berupa jaringan syaraf (*neural network*) yang digunakan untuk memparameterisasi inversi model transfer radiasi. Jaringan syaraf (NN) digunakan pada study ini sebagai teknik multiple nonlinier regresi. NN berupa model propagasi balik (*feedforward back propagation*) dengan dua lapisan tersembunyi. NN dilatih dengan komputasi radian dengan rentang konsentrasi untuk kloropil-a dari 0.001 s/d 64.0 $\mu\text{g/l}$, materi tersuspensi anorganik dari 0.01 s/d 50.0 mg/l , dan absorpsi CDOM pada panjang gelombang 440nm dari 0.001 s/d 5.0 m^{-1} . Sebagai input NN adalah radian dari lima kanal spektral MODIS yang telah dipilih sebelumnya. Keluarannya berupa konsentrasi tiga kandungan materi pokok air laut. Algoritma NN dites dengan data in-situ yang didapat pada bulan Mei, September dan Nopember tahun 2005 di sekitar Selat Badung Bali dan di laut sebelah utara Pulau Sumbawa dan diaplikasikan pada data

satelit MODIS. Didapat besar koefisien determinasi (R^2) antara klorofil-a hasil simulasi dengan data in-situ sebesar 0.327, untuk materi tersuspensi anorganik sebesar 0.408. Oleh karena tidak tersedia data in-situ untuk CDOM tidak dilakukan validasi. Data in-situ juga dibandingkan dengan algoritma standar dari NASA untuk klorofil-a MODIS OC4 (OC3M) memberikan nilai R^2 sebesar 0.188. Studi ini memberikan nilai akurasi lebih baik dari algoritma standar. Namun kedua algoritma masih memberikan nilai estimasi yang lebih tinggi. Oleh karena tidak ada produk standar untuk materi tersuspensi anorganik dan CDOM, hasil yang didapat dari jaringan syaraf untuk kedua variabel ini hanya dapat dibandingkan berdasarkan pengetahuan umum dan tafsiran tentang distribusi dan pola konsentrasi materi ini

Kata Kunci: Inverse Model, Jaringan Syaraf, Algoritma Ocean Color, Chlorophyll-a, Suspended Matter, CDOM, MODIS

INTRODUCTION

Coastal zones are attracting increasingly interest because they are the most populated and utilized areas of the earth. Over sixty percent of the human population lies in the coastal zone and about two third of worlds large cities are located along the coast (Parslow et al, 2000). Runoff and the delivery of nutrients and sediments to coastal waters are modified through human activities in catchments and shoreline. Development in coastal area leads to modify of foreshore, loss of key habitats such as mangroves and sea grasses, changes to flushing rate, resuspension of sediments, and direct inputs of nutrients and toxicants through outfall. The development of the ecological quality of these zones including the quality of the coastal water is a key issue of coastal zone management.

The coastal at Badung Strait Bali has an optically-complex water is recognized as case-2 waters, more complex in their composition and optical properties compare with simple case-1 waters or Open Ocean. Therefore the

interpretation of signal optic from case-2 waters becomes difficult. Recently, remote sensing of ocean color has focused largely on the relatively-simple case-1 waters, and it is well recognized that the standard algorithms in use today for chlorophyll retrieval from satellite data break down in case-2 waters (Sathyendranath, 2000). Satellite sensor to monitor ocean color by measure water-leaving radiance at a limited number of wavebands in the visible domain, and then to use the signal to infer concentrations of waters constituents such chlorophyll-a, inorganic suspended matters and colored dissolved organic matters in the near-surface layers of the ocean. The signals corrected for atmospheric noise (atmosphere correction) were then used in empirical algorithms (in-water algorithm) to retrieve concentrations like phytoplankton pigments (chlorophyll-a) might not work in coastal, and other optically-complex waters, where the presence of other substances such suspended matter and colored dissolved organic matter

(CDOM) might mask or modify the signal from phytoplankton pigment.

The color of water depends on scattering and absorption of visible light by pure water itself, by inorganic and organic, particulate and dissolved, material present in the water. These substances can vary independently of each other in case-2 waters, so must consider each of them separately. Furthermore, the color of case-2 waters may be influenced by bottom effect reflectance in shallow, clear waters, and specific atmospheric correction procedures that follow from the properties of case-2 waters. For these cases it is difficult to separate the influence of each substance, therefore algorithm based on empirical derived color ratios are insufficient with a complex and highly non-linear system. (Doerffer and Schiller, 1997). Development in water algorithm model-based approaches to separation of the three groups of substances has been developed using inverse modeling, its mean retrieving the concentrations of the components from the remotely-sensed radiance reflectance signal (Sathyendranath, 2000). Complex multiple non-linear regression problems can be done with Artificial Neural Network method (Doerffer and Schiller, 1997; Tanaka et al, 1998).

The purpose of this study, to use artificial neural network as inverting to estimate concentration of water constituents at Badung Strait Bali from water leaving radiance of five

visible band spectral of MODIS (Moderate Resolution Imaging Spectroradiometer). Data. The results were evaluated with the same day in-situ data set of the distribution of chlorophyll-a and turbidity data at Badung Strait Bali and north coast of Sumbawa island on May, September, November 2005.

RESEACH METHOD

Inverse Model

The first step in learning to interpret the ocean-color signal is to understand how to express the remotely-detected signal as a function of the concentrations of the various substances present in the water column. One can think of this as the forward modeling problem, and the inverse modeling problem is retrieving the concentrations of the components from the remotely-sensed signal.

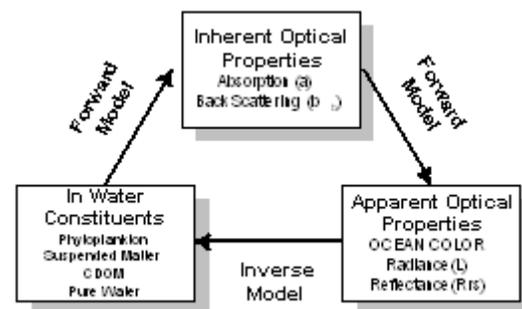


Figure 2.1 Interpretation Method of Ocean Color Signal

Computation of Water Leaving Radiance

Normalized of water leaving radiance is defined as:

$$[L_w(\lambda)]_n = F_0(\lambda) \frac{[\rho_w(\lambda)]_n}{\pi} \quad (1)$$

Where, F_0 is extra terrestrial solar irradiance (Thuillier et. al 2002). The relationship between normalized of water leaving reflectance and remote sensing reflectance is

$$[\rho_w(\lambda)]_n = \pi(t/n)^2 R_{rs}(\lambda) \quad (2)$$

Where, t is transmittance of upward radiance and downward irradiance across the sea surface. n is refractive index of salt water $(t/n)^2$ value is 0.544 (Austin, 1974). R_{rs} is related reflectance (R) that is ratio of upward and downward irradiance (Lee, et.al 1994).

$$R_{rs}(\lambda) = 0.533R(\lambda)/Q \quad (3)$$

Q is irradiance radiance ratio. $Q = 4.5$

$R(\lambda)$ can be expressed as (Joseph, 1950)

$$R(\lambda) = \frac{k(\lambda) - a(\lambda)}{k(\lambda) + a(\lambda)} \quad (4)$$

Where $k(\lambda)$ is attenuation coefficient, function of total absorption $a(\lambda)$ and backscattering coefficient $b_b(\lambda)$.

$$k(\lambda) = \sqrt{a(\lambda)[a(\lambda) + 2.0b_b(\lambda)]} \quad (5)$$

$a(\lambda)$ is contributed by water $a_w(\lambda)$ (Pope and Fry, 1997), chlorophyll-a $a_c(\lambda)$ proportional with concentration and CDOM $a_y(\lambda)$.

$$a(\lambda) = a_w(\lambda) + a_c(\lambda, chl) + a_y(\lambda, a_y(440)) \quad (6)$$

$a_y(\lambda)$ can be expressed as (Bricaud et.al, 1983)

$$a_y(\lambda) = a_y(440) \cdot \exp\{-0.014 \cdot (\lambda - 440)\} \quad (7)$$

$b_b(\lambda)$ is sum of backscattering coefficient

$$b_b(\lambda) = b_{bw}(\lambda) + b_{bc}(\lambda, chl) + b_{bs}(\lambda, SS) \quad (8)$$

Water $b_{bw}(\lambda)$ (Smith and Beker, 1981),

Chlorophyll-a $b_{bc}(\lambda)$ (Mobly, 1994)

$$b_{bc}(\lambda) = 0.0087 \times b_c(\lambda) \quad (9)$$

$$b_c(\lambda) = 0.27 \times chl^{0.698} \left(\frac{550}{\lambda} \right)^{-0.2983} \quad (10)$$

and suspended matter $b_{bs}(\lambda)$ (Fischer and Kronfeld, 1986)

$$b_{bs}(\lambda) = b_s(\lambda) \cdot 0.01478 \quad (11)$$

$$b_s(\lambda) = 0.125 \cdot SS \cdot \left(\frac{\lambda}{550} \right)^{-0.812} \quad (12)$$

With concentrations range in log scale from 0.001-64 $\mu\text{g/l}$ of chlorophyll-a, 0.01-50 mg/l of suspended matter, and CDOM absorption at 440nm of 0.001-5 m^{-1} and wavelength (λ) 412, 443, 488, 531, 551 nm mixture of concentration are made by constellation of 110.592 data set of normalized water leaving radiance, constructively by FORTRAN.

Neural Network Simulation

The Artificial Neural Network (ANN) adopted the feed-forward back propagation model, which was good for the optimization and computation. The feed-forward model consists of input layers, output layers and one or some hidden layers between them. Each layer consists of several neurons, and each neuron is linked to neurons in neighborhood layers with different

weights and biases. The information from input layers is feed-forwarded through processing neurons in hidden layer to the output neurons. The output value O of each neuron is calculated by:

$$O = S(-bias + \sum x_i w_i) \quad (13)$$

where, $bias$ is a specific value for each 'neuron', X_i is output value of neuron in the former layer, W_i is the weight of incoming-link, S is the Sigmoid tangential function as follows:

$$s(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)} \quad (14)$$

where, x is the activation value (i.e. the scalar product of the synaptic weight and input vector). The ANN was trained by the error back propagation procedure to adjust the biases and the weights of link. By using the 'training set', the ANN training is repeated until the mean squared error (MSE) being minimum. The MSE is defined as follows:

$$MSE = \frac{1}{n} \sum_{output} (NN_{output} - true_{value})^2 \quad (15)$$

Simulation is do by preparations phase and operations phase.

Preparations of Simulation

The data sets is separated randomly uniform distribution for two data sets, i.e. training sets (88.474) for teaching, and test set (22.118) for validation during the ANN training. All parameters are rescaled into a [-1, 1] amplitude before training the neural networks. Bias and weight is generated randomly balance. Inputs are

normalized water leaving radiance, output are concentration of water constituents.

Operation of Simulation

Each of these sets was then applied to the MatLab. The following network specific parameters were used: Learning function Gradient descent with momentum. Learning rate: 0.2 momentums: 0.8. Training function was used according to Levenberg-Marquardt optimization. Network training will stop by stopping procedure after a given MSE: 0.001.

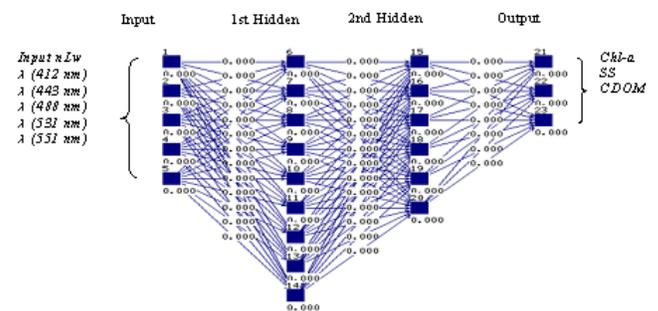


Figure 2.2 Artificial Neural Network

Field Observation Data

The measurement distribution of Chlorophyll-a and turbidity concentration at Badung Strait Bali W115.05 E115.63 N-8.41 S-8.89 (59 points) and north coast of Sumbawa island W115.05 E115.63 N-8.0 S-8.89 (152 points) is done on May 2-12, September 5-9, and November 14-18 2005. The north coast of Sumbawa island observation is included in this study in case of getting good validation. Bali

island and Sumbawa island has similar latitude. Equipments for water quality check are WQC-22A/24 TOA-DK and Compact-CTD ACTD 650/687 Alec electronic. In-situ data are used to validation of ANN simulation results.



Figure 2.3 (a) Water quality check WQC-24 TOA-DK and (b) Compact-CTD ACTD 687 Alec electronic

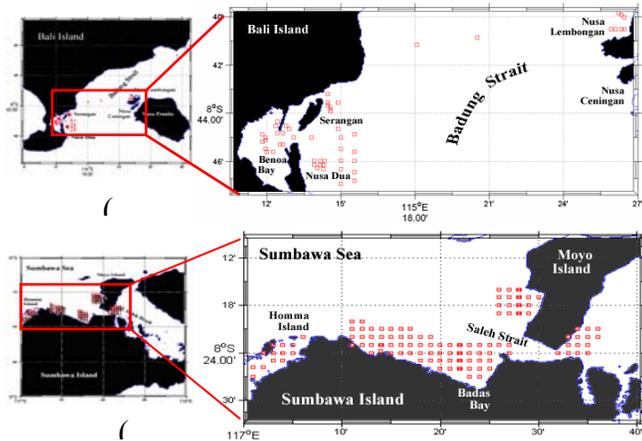


Figure 2.4 Stations of Sampling Data (a) Bali (b) Sumbawa

Satellite Data

MODIS (Moderate Resolution Imaging Spectrometer) satellite data with radiometric calibrated and geolocated radiances L1B 1km swath data are use for application. Date of acquisitions is synchronous with date of field observation. Satellite data is processed to level-2

products by SeaDas software. Atmosphere corrections are selected of four algorithms to get minimum negative water leaving radiance. The models are, (a).Multi-scattering fix model coastal 70% humidity, (b).Multi-scattering with 765/865 nm model, (c).Multi-scattering with 765/865 nm and NIR 10 time iteration, (d).Multi-scattering with 765/865 nm and NIR 50 time iteration. Products are normalized water leaving radiance which as input to ANN. Also, OC3M for chlorophyll-a product provide by NASA standard algorithm is used for comparison with in-situ data.

RESULT AND DISCUSSION

Computation of water leaving radiance is giving unique characteristic curve of absorption, backscattering and normalized water leaving radiance $(Lw)_N$ with separately concentration of three water constituents.

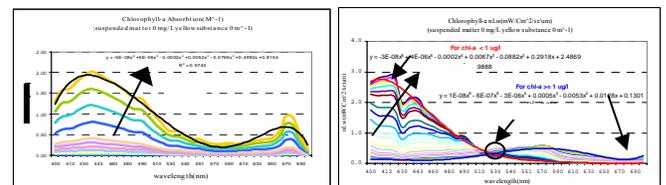


Figure 3.1 Curve characteristic of chlorophyll-a (a) Absorption (b) Radiance

Chlorophyll has two peak absorption (figure 3.1 a), fist is pigment peak at 440 nm ($50 \mu\text{g/l} \sim 2.01 \text{ m}^{-1}$) and second is fluorescent peak at 665 nm ($50 \mu\text{g/l} \sim 0.945 \text{ m}^{-1}$). Radiance has two type curve (figure 3.1b), less concentration than $1.0 \mu\text{g/l}$ and equal and greater concentration than $1.0 \mu\text{g/l}$. Curve characteristic cross at 530 nm.

Figure 3.2 showed radiance curve characteristic of suspended matter and CDOM with various concentration. Both has similar characteristic, energy is exponentially decreasing toward longer wavelength.

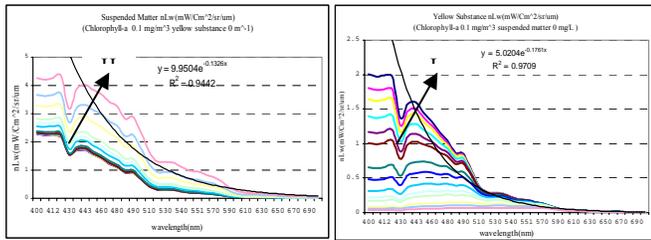


Figure 3.2 Radiance Curve characteristic of (a) Suspended matter (b) CDOM

ANN training has 259 epochs and MSE is 0.000999505. Test is giving good correlation result. Coefficient determination (R^2) for test of all substance is above 0.81 (Figure 3.3a-c). This network is valid for simulation

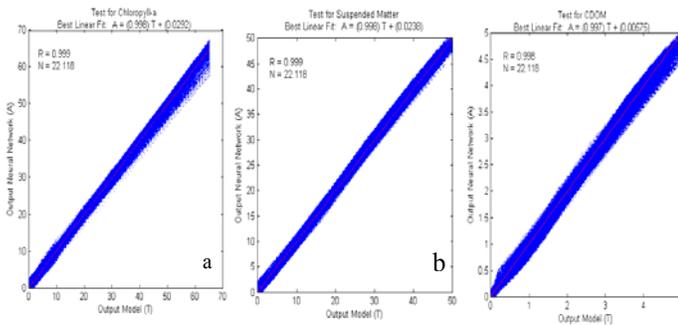


Figure 3.3 ANN test results. (a) Chlorophyll-a (b) Suspended matter (c) CDOM

Field observation result for distribution of chlorophyll-a and turbidity are showed in contour map (Figure 3.4a-d). At Badung Strait Bali

Chlorophyll with range 0.01-35.1 μ g/l, turbidity with range 0.1-7.7 mg/l. At North Coast of Sumbawa Chlorophyll with range 0.01-36.51 μ g/l, turbidity with range 0.00-13.84mg/l. Measurement at surface layer (less than 1 m).

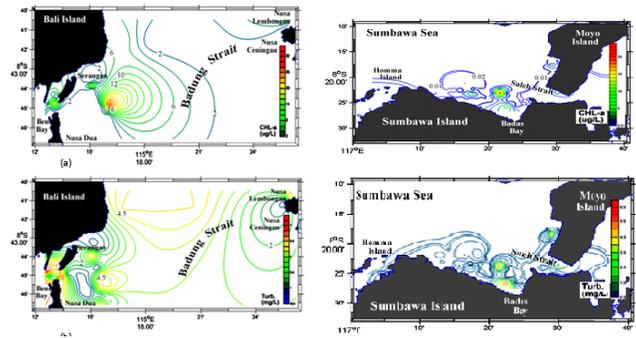


Figure 3.4 Distribution of chlorophyll-a (a), turbidity (b) Bali and Sumbawa (c-d).

Selection of atmosphere correction gives algorithm-d is less negative water leaving radiance (6.77% pixels). Algorithm-c gives 6.80% pixels of negative Lw (figure 3.5a), but gives 44 second faster than algorithm-d (figure 3.5b).

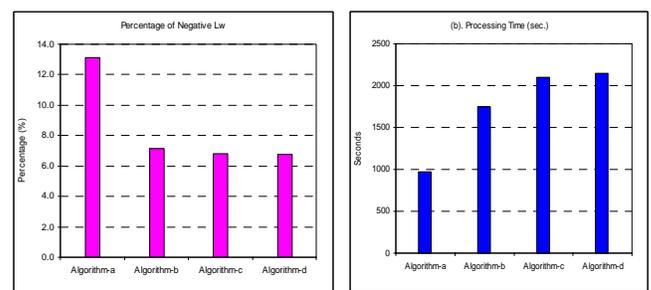


Figure 3.5 Percentages of nLw (a) and Processing Times (b) of Algorithms

Estimate concentration for chlorophyll-a, minimum is 0.001 maximum is 35.10 μ g/l. For suspended matter, estimate concentration

minimum is 0.01 maximum is 7.7 mg/l. For CDOM, estimate concentration minimum is 0.001 maximum is 5.0 mg/l. Distribution concentrations in detail are shown in figure 3.6.

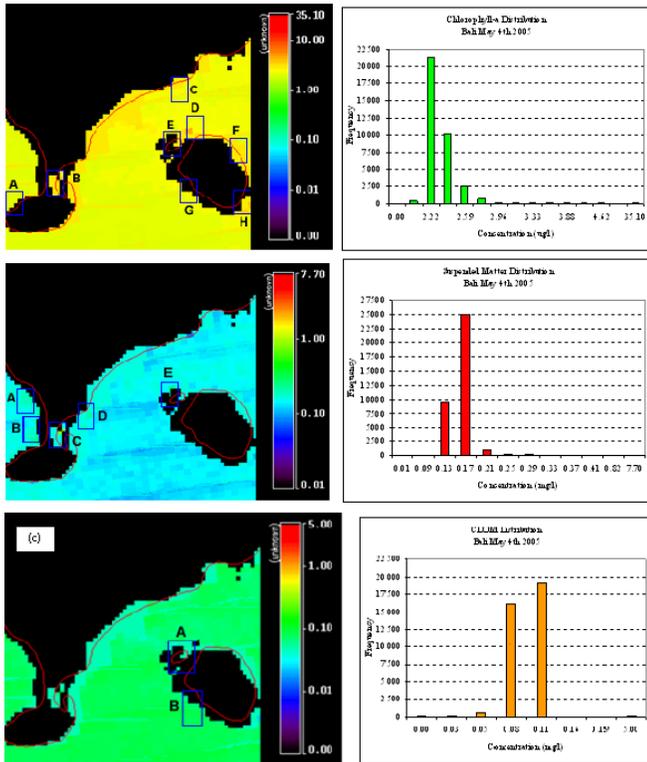


Figure 3.6 Distributions of Chlorophyll-a (a), Suspended matter (b) and CDOM (c)

from inverse model at Bali area May 4th 2005

Only 49 (23.22 %) data are selected can be use for validation, because cloud coverage on site and lack of satellite data. Comparison between in-situ and simulation result is giving R^2 0.3276 for chlorophyll and 0.4086 for turbidity. No in-situ measurement for CDOM For chlorophyll-a RMS is 1.473 $\mu\text{g/l}$, for suspended matter RMS is 1.319 mg/l. Comparison with another study is used OC3M chlorophyll-a empirical algorithm provide

by NASA as standard algorithm gives R^2 0.1884 with RMS is 1.325 $\mu\text{g/l}$.

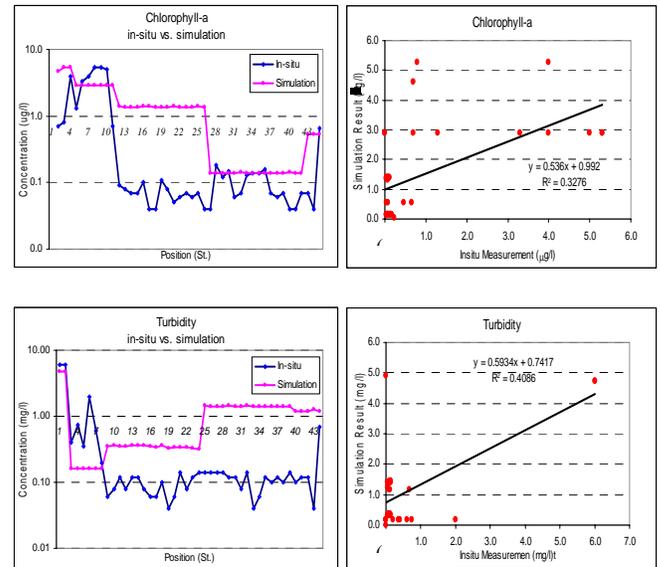


Figure 3.7 Comparison between in-situ and simulation (a) chlorophyll (b) suspended matter

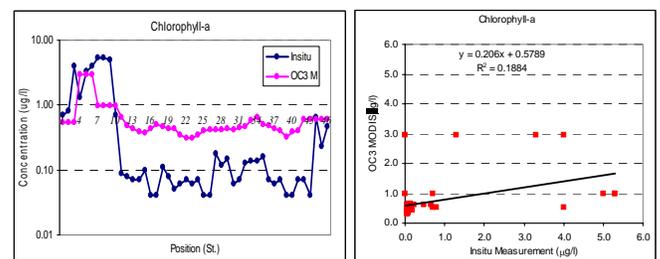


Figure 3.8 Comparison between in-situ and OC3M chlorophyll-a

Less accuracy of validation causes by some reasons. Like measurement technique, atmosphere condition and synchronized acquisitions between measurement and satellite images, so getting match-ups data is difficult. Those are main problem in passive ocean color. Output simulation is higher compared with in-situ data. In-situ data is

more varies and fluctuation compared with output simulation. The reason is due to concentration of substance (chlorophyll-a, suspended matter) obtained from satellite data is not just for surface value, actually it is an average effect in light penetrating zone. Atmosphere condition, like thin cloud and present of aerosol are also influence of magnitude of radiance which detect by sensor become high, therefore chlorophyll-a concentration obtained from satellite higher than in-situ data. Another reason is difference method used to detect concentration of the substance between satellite and in-situ measurement. This study used radiance reflected method as phytoplankton pigment to detect concentration of the substance, while in-situ measurement for chlorophyll-a used fluorescence line height method. Construct the vertical profile distribution pattern chlorophyll-a with considering the light penetrating in the site research location, develop validation protocol by use HPLC (high performance liquid Chromatography) analysis to measure chlorophyll-a concentration and gravimetric to inorganic suspended matter, improved of atmosphere correction algorithm are important to be carried out for accuracy of validating results. Reason about in-situ data more varying and fluctuation compared with output simulation, because transect of the stations doesn't agree with spatial resolution of the satellite data, where minimum distance for each stations must

more than 1 km. One pixel (1.000 m²) has same concentration of substance.

CONCLUSION

In this study, it is described that, multi-scattering with 765/865 nm and NIR 10 time iteration is the best selection for reduce negative water leaving radiance in case of coastal around Indonesia. Back propagation artificial neural network has ability to solve inverse problem with three unknown water constituent such as chlorophyll-a, suspended matter and colored dissolved organic matter (CDOM), from five normalized water leaving radiance in the visible bands. From case-1 oligotrophic to case-2 turbid water. Back propagation artificial neural network needs training process before applied to the satellite data. OC3M empirical algorithm as NASA standard algorithm for chlorophyll-a with in-situ data gives R^2 0.1884, this study gives better accuracy with R^2 0.327. How ever, both studies are still giving over estimate concentration.

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