An improved analytical algorithm for remote estimation of chlorophyll-a in highly turbid waters

Linhai Li¹,¹, Lin Li¹, Kaishan Song¹,², Yunmei Li³, Kun Shi¹,³ and Zuchuan Li¹

¹ Department of Earth Sciences, Indiana University–Purdue University Indianapolis, 723 West Michigan Street, SL 118, Indianapolis, IN 46202, USA
² Northeast Institute of Geography and Agricultural Ecology, CAS, Changchun, Jilin 130012, People’s Republic of China
³ Key Laboratory of Virtual Geographic Environment, Ministry of Education, College of Geographic Sciences, Nanjing Normal University, Nanjing 210046, People’s Republic of China

E-mail: lili032@ucsd.edu (L Li)

Received 10 March 2011
Accepted for publication 12 September 2011
Published 27 September 2011
Online at stacks.iop.org/ERL/6/034037

Abstract

An analytical three-band algorithm for spectrally estimating chlorophyll-a (Chl-a) has been proposed recently and the model does not need to be trained. However, the model did not consider the effects of the absorption due to colored detritus matter (CDM) and backscattering of the water column, resulting in an overestimation when Chl-a < 50 mg m⁻³ and an underestimation when Chl-a ≥ 50 mg m⁻³. In this letter, an improved three-band algorithm is proposed by integrating both backscattering and CDM absorption coefficients into the model. The results demonstrate that the improved three-band model resulted in more accurate estimation of Chl-a than the previously used three-band model when they were applied to water samples collected from five highly turbid water bodies with Chl-a ranging from 2.54 to 285.8 mg m⁻³. The best results, after model modification, were observed in three Indiana reservoirs with $R^2 = 0.905$ and relative root mean square error of 20.7%, respectively.

Keywords: chlorophyll-a, remote sensing, turbid waters, MERIS, inherent optical properties

1. Introduction

Human activities have resulted in significant negative effects on the water quality of reservoirs, lakes and estuaries (Matthews et al 2010, Simis et al 2007) as indicated by the increasing occurrence of algal blooms, especially toxic cyanobacterial blooms (Matthews et al 2010, Simis et al 2005, 2007). Remote sensing techniques have been considered for timely efficient monitoring approach of inland waters (Becker et al 2009, Jupp et al 1994). However, the optical complexity of case 2 waters makes it difficult to spectrally retrieve chlorophyll-a (Chl-a), an index of trophic status of inland waters. This difficulty results from high concentration of non-algal particles (NAP) and colored dissolved organic matter (CDOM) in case 2 water as compared to case 1 waters (Schalles et al 2001, Schalles 2006). Among many empirical or semi-empirical algorithms, three-band algorithms have been widely used for estimation of Chl-a in inland waters because of its capability of accommodating the influence of NAP and CDOM on the estimation. The three-band spectral index shown in equation (1) is expressed as a simple algebra operation of remote sensing reflectance, RS(λ), in three
spectral bands (Dall’Olmo et al. 2003):

\[
\text{Chl-a} \propto [\text{RS}(\lambda_1)^{-1} - \text{RS}(\lambda_2)^{-1}] \times \text{RS}(\lambda_3)
\]  

(1)

RS(λ) includes both below water subsurface remote sensing reflectance \(r_a(\lambda)\) and above water surface remote sensing reflectance \(R_\text{rs}(\lambda)\), and \(R_\text{rs}(\lambda) = 0.54r_a(\lambda)\) (Gons et al. 2005). \(r_a(\lambda)\) can be related to the inherent optical properties of inland waters as shown in equation (2) (Gordon et al. 1988):

\[
r_a(\lambda) = C(\lambda) \frac{b_\text{ph}(\lambda)}{a(\lambda)} + b_\text{w}(\lambda)
\]  

(2)

where \(C(\lambda)\) is a variable depending on wavelength \(\lambda\) for a given sample location, \(a(\lambda)\) is the sum of the absorption coefficients of phytoplankton pigments, \(a_{\text{ph}}(\lambda)\), colored detritus matters (CDM = CDOM + NAP), \(a_{\text{cdm}}(\lambda)\), and pure water, \(a_w(\lambda)\). While three-band algorithms performed well in many studies (Gitelson et al. 2007, 2008, 2009, Hunter et al. 2010, Moses et al. 2009, Yacobi et al. 2011), it does require calibration to achieve an accurate prediction of Chl-a when applying to new dataset, which involves with optimization of spectral bands and regression coefficients. Duan et al. (2010) recently decomposed the algorithm with detailed bio-optical interpretation, but calibration is still required by linear least square regression. Gilerson et al. (2010) recently proposed a universal three-band algorithm with the aim of minimizing the influences of backscattering and CDM absorption on the Chl-a estimation and improving the performance of the three-band algorithm for retrieving Chl-a from various spectral datasets collected in highly turbid and eutrophic waters.

2. Data and methods

2.1. Data

Field data were collected in Shitoukoumen Reservoir (Northeast China, 43°54’6”N, 125°46.95’E) from 2006 to 2008, Lake Tai (Middle-east China, 30°56’-31°33’N, 119°53.3’-120°53.6’E) from 2006 to 2007 and three central Indiana reservoirs, Eagle Creek reservoir (39°51’N, 86°18.3’W), Geist reservoir (39°55’N, 85°56.7’W) and Morse reservoir (40°6.4’N, 86°2.3’W) in 2008. \(R_\text{rs}(\lambda)\) was measured with ASD field spectrometer (Analytical Spectral Devices, Inc. Boulder, CO, USA) at each station of Shitoukoumen reservoir and Lake Tai by following NASA protocols (Mueller et al. 2003) with radiometer about 2 m above surface. Below water surface spectral reflectance \(r_a(\lambda)\) in three central Indiana reservoirs was measured with Ocean Optics USB4000 (Ocean Optics, Inc., Dunedin, FL, USA) by following the procedures recommended by Gitelson et al. (2007) with radiometer dipped about 2–3 cm below surface. Chl-a was extracted using 90% acetone and its concentration was determined with a Shimadzu UV2401 spectrophotometer (Shimadzu, Inc., Tokyo, Japan). Concentrations of total suspended matters (TSM) were measured gravimetrically. Figure 1 shows the in situ measured remote sensing reflectance spectra, and the range and mean for the Chl-a and TSM concentration of the samples collected in the three study regions are shown in table 1.

2.2. Method

We propose to expand the three-band index \(R_3\) used in equation (3) into (4):

\[
R_3 = \frac{b_\text{ph}(753)}{a_w(753) + a_{\text{cdm}}(753) + a_{\text{ph}}(753) + b_\text{w}(753)} \times \left[ \frac{a_w(665) + a_{\text{cdm}}(665) + a_{\text{ph}}(665) + b_\text{w}(665)}{b_\text{ph}(665)} \right] - \frac{a_w(708) + a_{\text{cdm}}(708) + a_{\text{ph}}(708) + b_\text{w}(708)}{b_\text{ph}(708)}.
\]  

(4)

With the same assumption used in previous studies, i.e. that \(b_\text{w}(665)\), \(b_\text{w}(708)\) and \(b_\text{w}(753)\) are not significantly different (Duan et al. 2010, Gilerson et al. 2010), and \(a_{\text{ph}}(708)\), \(a_{\text{cdm}}(753)\) and \(a_{\text{ph}}(753)\) are negligible (Gilerson et al. 2010), equation (4) can be simplified as:

\[
R_3 = \frac{a_{\text{ph}}(665) + a_{\text{cdm}}(665) - a_{\text{cdm}}(708) + a_w(665) - a_w(708)}{a_w(753) + b_\text{w}(753)}.
\]  

(5)

Meanwhile, \(a_{\text{ph}}(665)\) has relationship with Chl-a as equation (6) in which the relationship \(a_{\text{ph}}^*(665) = 0.022\text{Chl-a}^{1-p-1}\) is directly cited from Gilerson et al. (2010) with \(p\) as a constant.

\[
a_{\text{ph}}(665) = a_{\text{ph}}^*(665)\text{Chl-a} = 0.022\text{Chl-a}^p.
\]  

(6)

Subsequently, by combining equation (5) and (6), Chl-a can be determined using equation (7) (denoted as improved three-band algorithm, ITA) where \(p\) is set to 0.89 according to Gilerson et al. (2010).
Chl-a = \{[\alpha_{w}(753) + b_{w}(753)]R3 - \alpha_{w}(665) + a_{w}(708) - a_{cdm}(665) + a_{cdm}(708)\}[0.022]^{-1/3}.

(7)

The difference between ITA and G10 lies in that Gilerson et al (2010) assumed that \(b_{w}(753)\) is much less than \(a_{w}(753)\) and \(a_{cdm}(708) - a_{cdm}(665)\) approaches to 0, thus both variables are negligible in equation (3), but we emphasize that in highly turbid waters both \(b_{w}(753)\) and \(a_{cdm}(708) - a_{cdm}(665)\) have significant impacts on the estimation of Chl-a.

To apply equation (7) for Chl-a estimation, \(b_{w}(753)\) and \(a_{cdm}(708) - a_{cdm}(665)\) should be derived. We propose to use the method by Gons et al (2005) to derive \(b_{w}(753)\) from \(r_{sl}(753)\) (equation (8)) or from \(R_{w}(753)\) (equation (9)). Both equations are derived from equation (2) and based on relationship that \(a(\lambda) \approx a_{w}(753)\) and assumption that \(C(753) = 0.82\). According to Gons et al (2005) and Simis et al (2005), \(C(778) = 0.082\) is realistic for inland waters, although it is more complicatedly related to several factors, e.g. sun angle, viewing geometry. In this letter, it is assumed that \(C(753) \approx C(778)\) since band 753 nm is closed to band 778 nm. However, more studies on values of \(C(\lambda)\) are required, if possible, in the future.

\[ b_{w}(753) = \frac{\alpha_{w}(753)r_{sl}(753)}{0.082 - r_{sl}(753)} \]

(8)

\[ b_{w}(753) = \frac{1.852a_{w}(753)R_{w}(753)}{0.082 - 1.852R_{w}(753)} \]

(9)

For turbid waters, it is well known that the absorption of CDM can be modeled by the following equation:

\[ a_{cdm}(\lambda) = a_{cdm}(440) \exp[-S_{cdm} \times (\lambda - 440)]. \]

(10)

Given \(a_{cdm}(440)\) and \(S_{cdm}\) have typical average values for most of turbid inland waters, i.e. \(a_{cdm}(440) = 2 \text{ m}^{-1}\) and \(S_{cdm} = 0.015 \text{ nm}^{-1}\), \(a_{cdm}(708) - a_{cdm}(665)\) is calculated to be 0.0325 \text{ m}^{-1} using equation (10).

The prediction accuracy of Chl-a is evaluated by the coefficient of determination \((R^2)\), relative error, and relative root mean square error (rRMSE) which are defined as:

\[ \text{relative error} = \frac{\hat{X}_i - X_i}{X_i} \]

(11)

\[ \text{rRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{X}_i - X_i)^2} \times 100\% \]

(12)

where \(\hat{X}_i\) is the estimated value and \(X_i\) is the measured value for sample \(i\).

3. Results and discussion

3.1. Model comparison

Comparison between measured and estimated Chl-a for Shitoukoumen reservoir, Lake Tai and three Indiana reservoirs is shown in figure 2 and table 2. The proposed ITA performs better than that by G10 (see figure 2 and table 2). It is apparent that ITA results in correlations between measured and estimated Chl-a closer to 1:1 line, higher \(R^2\) and lower rRMSE than those resulting from G10. Our model shows significantly improved estimation of Chl-a for samples collected in both Lake Tai and three Indiana reservoirs. Even for samples from Shitoukoumen reservoir, the improvement of ITA over G10...
Figure 2. Comparison between measured Chl-a and estimated Chl-a for Shitoukoumen reservoir ((a), (d)), Lake Tai ((b), (e)) and three Indiana reservoirs ((c), (f)). The results from ITA are shown in the left column and those from G10 in the right column.

Table 2. Comparison between the results for estimated Chl-a where slope and $R^2$ are determined by forcing a zero intercept.

|                  | Shitoukoumen reservoir ($n = 137$) | Lake Tai ($n = 45$) | Indiana reservoirs ($n = 65$) |
|------------------|-------------------------------------|---------------------|--------------------------------|
|                  | Slope     | $R^2$   | rRMSE | Slope     | $R^2$   | rRMSE | Slope     | $R^2$   | rRMSE |
| G10              | 1.178     | 0.597   | 43.3%  | 0.770     | 0.639   | 52.6%  | 0.919     | 0.873   | 21.8%  |
| ITA              | 1.106     | 0.710   | 41.2%  | 1.086     | 0.931   | 34.6%  | 1.040     | 0.905   | 20.7%  |
is evident, i.e. $R^2$ increases from 0.597 to 0.710 and rRMSE decreases from 43.3% to 41.2%.

The advantage of ITA can also be appreciated by examining the relative error, an indicator of bias in estimated Chl-a. Figure 3 shows that G10 results in an overestimation for samples with Chl-a $< 50$ mg m$^{-3}$ and underestimation for samples with Chl-a $\geq 50$ mg m$^{-3}$, but this estimation bias was significantly reduced and overall estimation tends to be more closed to ground measurements (figure 3) when the ITA was applied. Figure 4 exhibits that relative errors resulting from ITA distribute nearly normally, while those from G10 have a skew distribution to a positive bias.

### 3.2. Significance of $b_b(753)$ and $a_{cdm}(\lambda)$ for Chl-a estimation

Remote sensing reflectance spectra used in this study have similar shapes to those collected in other turbid productive waters (Duan et al 2010, Gitelson et al 2009, and references therein), but they do demonstrate much larger reflectance magnitudes at wavelengths longer than 750 nm than those spectra presented in Gitelson et al (2009). This indicates that the waters examined in this study are highly turbid due to abundant suspended particles that significantly contribute the RS($\lambda$) in the near-infrared region. As shown in table 1, $b_b(753)$ can be as high as 5.82 m$^{-1}$, more than twice of $a_w(753)$, and it is not surprising that ignoring high $b_b(753)$ results in large uncertainty in estimated Chl-a as shown in figures 2 and 3.

While $a_{cdm}(665) - a_{cdm}(708)$ has insignificant effect on the estimation of Chl-a when Chl-a concentration is high, failing to accommodate the effect of $a_{cdm}(665) - a_{cdm}(708)$ could lead to dramatic estimation errors when Chl-a is low because $a_{ph}(665)$ is also relatively small. Our modeling results (not shown here) also indicate that only correcting for the effect of $b_b(753)$ is not sufficient for samples with Chl-a $\leq 20$ mg m$^{-3}$. In addition, ITA resulted in large magnitude relative errors ($\sim -1$) for some samples (Chl-a $\leq 20$ mg m$^{-3}$) from Shitoukoumen reservoir, which suggests that although $a_{cdm}(665) - a_{cdm}(708) = 0.0325$ m$^{-1}$ works well for most samples used in this study, this value may not be suitable for low Chl-a samples from Shitoukoumen reservoir.

To further improve the performance of the current three-band model, a robust retrieval model for modeling $a_{cdm}(\lambda)$ is required. The results for samples from Shitoukoumen reservoir also imply that it is very difficult to accurately estimate Chl-a in such extremely turbid water bodies, e.g. for waters with TSM up to 211.91 g m$^{-3}$. Nonetheless, the current ITA does show high performance and perform better than G10 for all...
Figure 4. Relative error distribution, negative values mean overestimation and vice versa. (a) Shitoukoumen reservoir; (b) Lake Tai; (c) three Indiana reservoirs.

study sites, especially for Lake Tai and three Indiana reservoirs where TSM is relatively low (table 1).

4. Conclusions

An improved three-band model is proposed and tested with the datasets of water samples collected from two China lakes, Shitoukoumen reservoir and Lake Tai, and three central Indiana reservoirs. Our results demonstrate that the model by G10 can result in significant overestimation for samples with Chl-a < 50 mg m\(^{-3}\) and underestimation for samples with Chl-a ≥ 50 mg m\(^{-3}\). However, the correction for the effects of \(b_h(753)\) and \(a_{clm}(\lambda)\) results in an improved three-band model which works well with three data sets collected over five different reservoirs and lakes with Chl-a covering from 2.54 mg m\(^{-3}\) to 285.8 mg m\(^{-3}\) and TSM from 1.51 g m\(^{-3}\) to 211.91 g m\(^{-3}\), respectively. Therefore, it should be preferred over other three-band algorithms for estimating Chl-a from satellite image spectra such as MERIS data.

Acknowledgments

We thank Center of Earth and Environmental Sciences (CEES), Indiana University–Purdue University at Indianapolis (IUPUI), for assisting field water sampling in three central Indiana reservoirs. The authors appreciate the financial support by the NASA Energy and Water Cycle Study program (Grant No. NNX09AU87G).

References

Becker R H, Sultan M I, Boyer G L, Twiss M R and Konopko E 2009 Mapping cyanobacterial blooms in the great lakes using modis J. Great Lakes Res. 35 447–53

Dall’Olmo G, Gitelson A A and Rundquist D C 2003 Towards a unified approach for remote estimation of chlorophyll-a in both terrestrial vegetation and turbid productive waters Geophys. Res. Lett. 30 1938–41

Duan H T, Ma R, Zhang Y, Loiselie S A, Xu J, Zhao C, Zhou L and Shang L 2010 A new three-band algorithm for estimating chlorophyll concentrations in turbid inland lakes Environ. Res. Lett. 5 044009

Gilerson A, Zhou J, Hlaing S, Ioannou I, Schalles J, Gross B, Moshary F and Ahmed S 2007 Fluorescence component in the reflectance spectra from coastal waters. Dependence on water composition Opt. Express 15 15702–21

Gilerson A A, Dall’Olmo G, Moses W, Rundquist D C, Barrow T, Fisher T R, Gurlin D and Holz J 2008 A simple semi-analytical model for remote estimation of chlorophyll-a in turbid waters: validation Remote Sens. Environ. 112 3582–93

Gilerson A A, Gitelson A A, Zhou J, Gurlin D, Moses W, Ioannou I and Ahmed S A 2010 Algorithms for remote estimation of chlorophyll-a in coastal and inland waters using red and near infrared bands Opt. Express 18 24109–25

Gileron A A, Gurlin D, Moses W J and Barrow T 2009 A bio-optical algorithm for the remote estimation of the chlorophyll-a concentration in case 2 waters Environ. Res. Lett. 4 045003

Gileson A A, Schalles J F and Hiadid C M 2007 Remote chlorophyll-a retrieval in turbid, productive estuaries: Chesapeake bay case study Remote Sens. Environ. 109 464–72

Gons H J, Rijkeboer M and Ruddick K G 2005 Effect of a waveband shift on chlorophyll retrieval from meris imagery of inland and coastal waters J. Plankton Res. 27 125–7

Gordon H R, Brown O B, Evans R H, Brown J W, Smith R C, Baker K S and Clark D K 1988 A semi-analytic radiance model of ocean color J. Geophys. Res.-Atmos. 93 10909–24

Hunter P D, Tyler A N, Carvalho L, Codd G A and Maberly S C 2010 Hyperspectral remote sensing of cyanobacterial pigments as indicators for cell populations and toxins in eutrophic lakes Remote Sens. Environ. 114 2705–18

Jupp D L B, Kirk J T O and Harris G P 1994 Detection, identification and mapping of cyanobacteria—using remote-sensing to measure the optical-quality of turbid inland waters Aust. J. Mar. Fresh Water Res. 45 801–28

Matthews M W, Bernard S and Winter K 2010 Remote sensing of cyanobacteria–dominant algal blooms and water quality parameters in zeekoevlei, a small hypertrophic lake, using meris Remote Sens. Environ. 114 2070–87

Moses W J, Gitelson A A, Berdnikov S and Povazhnyy V 2009 Estimation of chlorophyll-a concentration in case II waters using MODIS and MERIS data—successes and challenges Environ. Res. Lett. 4 045005
Mueller J L, Fargion G S and Macclain C R 2003 *Ocean Optics: Protocols for Satellite Ocean Color Sensor Validation, Revision 4* (Greenbelt, MD: NASA)

Schalles J F 2006 Optical remote sensing techniques to estimate phytoplankton chlorophyll a concentrations in coastal waters with varying suspended matter and cdom concentrations *Remote Sensing of Aquatic Coastal Ecosystem Process: Science and Management Applications* ed L L Richardson and E F LeDrew (Berlin: Springer) pp 27–79

Schalles J F, Rundquist D C and Schiebe F R 2001 The influence of suspended clays on phytoplankton reflectance signatures and the remote sensing estimation of chlorophyll *Véran. Limnol. 27* 3619–25

Simis S G H, Peters S W M and Gons H J 2005 Remote sensing of the cyanobacterial pigment phycocyanin in turbid inland water *Limnol. Oceanogr. 50* 237–45

Simis S G H, Ruiz-Verdu A, Dominguez-Gomez J A, Pena-Martinez R, Peters S W M and Gons H J 2007 Influence of phytoplankton pigment composition on remote sensing of cyanobacterial biomass *Remote Sens. Environ. 106* 414–27

Smith R C and Baker K S 1981 Optical properties of the clearest natural waters (200–800 nm) *Appl. Opt. 20* 177–84

Yacobi Y Z, Moses W J, Kaganovsky S, Sulimani B, Leavitt B C and Gitelson A A 2011 NIR-red reflectance-based algorithms for chlorophyll a estimation in mesotrophic inland and coastal waters: Lakekinneret case study *Water Res. 45* 2428–36