Estimation of chlorophyll-a concentration in estuarine waters: case study of the Pearl River estuary, South China Sea

Yuanzhi Zhang\textsuperscript{1,6}, Hui Lin\textsuperscript{1}, Chuqun Chen\textsuperscript{2}, Liding Chen\textsuperscript{3}, Bing Zhang\textsuperscript{4} and Anatoly A Gitelson\textsuperscript{5}

\textsuperscript{1} Institute of Space and Earth Information Science, Yuen Yuen Research Centre for Satellite Remote Sensing, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong
\textsuperscript{2} South China Institute of Oceanology, Chinese Academy of Sciences, Guangzhou, People's Republic of China
\textsuperscript{3} Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing, People's Republic of China
\textsuperscript{4} Center for Earth Observation and Digital Earth, Chinese Academy of Sciences, Beijing, People's Republic of China
\textsuperscript{5} Center for Advanced Land Management Information Technologies (CALMIT), School of Natural Resources, University of Nebraska–Lincoln, USA

E-mail: yuanzhizhang@cuhk.edu.hk

Received 9 December 2010
Accepted for publication 17 May 2011
Published 1 June 2011
Online at stacks.iop.org/ERL/6/024016

Abstract
The objective of this work is to estimate chlorophyll-a (chl-a) concentration in the Pearl River estuary in China. To test the performance of algorithms for the estimation of the chl-a concentration in these productive turbid waters, the maximum band ratio (MBR) and near-infrared–red (NIR–red) models are used in this study. Specific focus is placed on (a) comparing the ability of the models to estimate chl-a in the range 1–12 mg m\textsuperscript{-3}, which is typical for coastal and estuarine waters, and (b) assessing the potential of the Moderate Resolution Imaging Spectrometer (MODIS) and Medium Resolution Imaging Spectrometer (MERIS) to estimate chl-a concentrations. Reflectance spectra and water samples were collected at 13 stations with chl-a ranging from 0.83 to 11.8 mg m\textsuperscript{-3} and total suspended matter from 9.9 to 21.5 g m\textsuperscript{-3}. A close relationship was found between chl-a concentration and total suspended matter concentration with the determining coefficient ($R^2$) above 0.89. The MBR calculated in the spectral bands of MODIS proved to be a good proxy for chl-a concentration ($R^2 > 0.93$). On the other hand, both the NIR–red three-band model, with wavebands around 665, 700, and 730 nm, and the NIR–red two-band model (with bands around 665 and 700 nm) explained more than 95% of the chl-a variation, and we were able to estimate chl-a concentrations with a root mean square error below 1 mg m\textsuperscript{-3}. The two- and three-band NIR–red models with MERIS spectral bands accounted for 93% of the chl-a variation. These findings imply that the extensive database of MODIS and MERIS images could be used to quantitatively monitor chl-a in the Pearl River estuary.

Keywords: chlorophyll, reflectance, remote sensing

1. Introduction

Remote estimation of the concentrations of water constituents is based on the relationship between the spectral reflectance, $\rho_r(\lambda)$, and the inherent optical properties, the backscattering coefficient, $b_b(\lambda)$, and the absorption coefficient, $a(\lambda)$ (Gordon \textit{et al} 1975):

$$\rho_r(\lambda) \propto \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}, \quad (1)$$
where $a(\lambda)$ is the sum of the absorption coefficients of phytoplankton pigments, $a_{\text{pig}}$, coloured dissolved organic matter, $a_{\text{CDOM}}$, non-algal particles, $a_{\text{NAP}}$, and pure water, $a_{\text{water}}$. To retrieve the chl-a concentration from spectral reflectance, the chl-a absorption coefficient has to be isolated. For open ocean Case 1 waters (Morel and Prieur 1977), reflectance in the blue and green spectral regions used to be employed (e.g. Gordon and Morel 1983, Kirk 1994, Mobley 1994). The maximum band ratio (MBR), calculated as the maximum of three-band reflectance ratios at wavelength 443, 490, 520, and 565 nm ($\rho_{443}/\rho_{565}$, $\rho_{490}/\rho_{565}$, $\rho_{520}/\rho_{565}$), was used to estimate chl-a concentrations in Case 1 ocean waters (e.g. O’Reilly et al 1998). In turbid productive Case 2 waters (Morel and Prieur 1977), these spectral regions cannot be used to estimate chl-a because of the overlapping, uncorrelated absorptions by coloured dissolved organic matter (CDOM) and non-algal particles (NAP), which are much larger in these waters (e.g. Gitelson 1992, Gons 1999, Dall’Olmo et al 2005).

The algorithms developed to estimate chl-a in turbid productive waters are based on reflectances in the red and near infrared (NIR) spectral region. Stumpf and Tyler (1988) suggested using the following ratio of reflectances:

$$\text{chl-a} \propto \frac{\rho_{\text{NIR}}}{\rho_{\text{red}}}$$

in the NIR and the red bands of the Advanced Very High Resolution Radiometer (AVHRR) and the Coastal Zone Color Scanner (CZCS) to identify phytoplankton blooms and provide estimates of chl-a concentrations above 10 mg m$^{-3}$ in turbid estuaries.

Most of the algorithms developed to quantify chl-a concentrations are based on the properties of the peak near 700 nm. These include the ratio of the reflectance peak ($\rho_{\text{max}}$) to the $\rho_{700}$, $\rho_{\text{max}}/\rho_{700}$, and a widely used two-band NIR-red model in the following form (Gitelson et al 1985, 1986, Gitelson and Kondrat’ev 1991, Gitelson 1992, Dekker 1993):

$$\text{chl-a} \propto \frac{\rho_{\text{NIR}}(705)}{\rho_{\text{NIR}}(670)}$$

Gons (1999) used the ratio of reflectances at 704 and 672 nm, with absorption and backscattering coefficients at these wavelengths to assess chl-a concentrations ranging from 3 to 185 mg m$^{-3}$. In many studies, close relationships have been found between chl-a concentration and NIR-to-red reflectance ratios, with the red wavelength around 675 nm and the NIR wavelength varying between 700 and 725 nm (e.g. Hoge et al 1987, Yakobi et al 1995, Pierson and Strömbäck 2000, Pulliainen et al 2001, Ruddick et al 2001, Oki and Yasuoka 2002, Dall’Olmo and Gitelson 2005a, 2005b).

A three-band reflectance model was developed for the estimation of pigment contents in terrestrial vegetation (Gitelson et al 2003). Dall’Olmo et al (2003) provided evidence that this model could also be used to assess chl-a concentration in turbid productive waters. The model relates the pigment concentration $C_{\text{pig}}$ to reflectance in three spectral bands $\lambda_i$:

$$C_{\text{pig}} \propto [\rho^{-1}(\lambda_1) - \rho^{-1}(\lambda_2)] \times \rho(\lambda_3).$$

It has been shown that to estimate phytoplankton chl-a concentration, $\lambda_1$ should be in the red range around 670 nm, $\lambda_2$ in the range 700–710 nm and $\lambda_3$ in the NIR range 730–750 nm (Dall’Olmo et al 2003, Dall’Olmo and Gitelson 2005a, 2005b, 2006, Gitelson et al 2007, 2008). The NIR-to-red ratio (equation (2)) is a special case of the three-band model when $\lambda_2 = \lambda_1$; chl-a $\propto (R_{\lambda_1}^{-1} - R_{\lambda_2}^{-1})$. The performance of the algorithms, developed based on equations (2)–(4), was evaluated using the spectral bands available on MERIS and this proved them to be a reliable tool (with chl-a estimation errors below 5 mg m$^{-3}$) for turbid productive waters with chl-a concentrations in the range of 2–120 mg m$^{-3}$ (Moses et al 2009a, 2009b, Gitelson et al 2011).

Recently, two modifications of the model (equation (4)) were published, both of which were used for the estimation of chl-a concentrations in productive waters with a very high concentration of inorganic suspended matter. Le et al (2009) suggested using a four-band model with narrow spectral bands, i.e.

$$\rho^{-1}(662) - \rho^{-1}(693)]/\rho^{-1}(740) - \rho^{-1}(705).$$

Yang et al (2010) presented a model in the following form:

$$\rho^{-1}(\lambda_1) - \rho^{-1}(\lambda_2)]/\rho^{-1}(\lambda_3) - \rho^{-1}(\lambda_3),$$

where $\lambda_1$, $\lambda_2$, and $\lambda_3$ are in the spectral bands of the MERIS system centred at 665, 708, and 753 nm, respectively. Both models showed a high level of accuracy in the estimation of chl-a in very turbid productive waters around China and Japan.

The objective of this paper is to estimate the chl-a concentration in the Pearl River estuary (PRE) in China. The PRE is a large source of freshwater that carries suspended sediments, particulates, dissolved organic matter, and nutrients into the South China Sea (see figure 1). In the PRE river, freshwater and sea water are mixed over a distance of a few kilometres, and the level of the highly saline stratification from the water surface to the bottom layer varies from 0 to 30%/o, and in particular reaches as much as 10.8%/o within 1 m of the halocline layer (Bao and Ren 2005).

Since the 1980s, with the rapid increase in urbanization in the Pearl River Delta (PRD) region, the PRE environment has suffered considerable damage from the activities in the urban areas, which greatly affected water quality, and the level of chl-a and total suspended solids (TSS) concentrations in the PRE have gradually been receiving more attention. Quantitative remote sensing analysis of chl-a and TSS in the PRE was successfully undertaken in the early 1990s (Li 1992). Data from various satellites such as Landsat TM and AVHRR were used to estimate chl-a and TSS concentrations by mean of different models (Liu et al 2005, Chen et al 2005). However, since most of the empirical relationships used in those models proved to be unsuitable for the PRE area, there was a need for an algorithm for chl-a estimation in this area to be developed. In this study, the focus is placed especially on (a) comparing the ability of the models used for Case 1 and Case 2 waters to estimate the chl-a concentration in the range 1–12 mg m$^{-3}$, which is typical for coastal and estuarine waters, and (b) assessing the potential of the Moderate Resolution Imaging Spectrometer (MODIS) and Medium Resolution Imaging Spectrometer (MERIS) to estimate the chl-a concentrations.
Figure 1. The location of water sampling stations in the study on 16 May 2008. Inset: concentration of chl-a in mg m$^{-3}$ and total suspended solids in g m$^{-3}$ are shown for each station as (chl-a/TSS).

2. Methods

One cruise was conducted in the middle part of the PRE on 16 May 2008. Figure 1 indicates the locations of 15 water sampling stations in the PRE. Reflectance spectra were measured using the SD2000 spectroradiometer with a spectral resolution of 0.37 nm calibrated to yield absolute values of radiance. The radiometer was then used to measure upward radiance ($L_u$) emitted from the water surface and sky radiance ($L_{sky}$) following the ocean optics protocols of Mueller et al (2003). Reflectance was calculated using $L_u$, $L_{sky}$; the grey plaque radiance ($L_{plaq}$) was used for calibration purposes (Mueller et al 2003).

Water samples were collected by a surface water collector at the same time as the field spectral measurements were made. The sampling depth was 0.5 m beneath the water surface. Water samples at the 15 stations were collected and refrigerated in a cold and dark container and processed several hours later in the laboratory. Chl-a concentrations were measured using the spectrophotometric determination method following the NASA ocean optics protocols. TSS concentrations were determined gravimetrically from samples collected on the pre-combusted and pre-weighed GF/F filters with a diameter of 47 mm, dried at 95 ºC overnight. Subsequently, the suspended matter concentrations were quantified by weighing the dry
3. Results and discussion

In the waters sampled, the chl-a concentrations varied from 0.83 to 11.77 mg m\(^{-3}\) and the TSS values from 9.94 to 21.52 g m\(^{-3}\). The TSS and chl-a concentrations were strongly correlated with the determination coefficient \(R^2\) above 0.88 (figure 2). However, as chl-a was below 2 mg m\(^{-3}\), relationship TSS versus chl-a was very weak (\(R^2 < 0.2\)); high concentrations of NAP governed the optical properties of these waters. Morel and Prieur (1977) defined an ideal Case 1 water as pure culture of phytoplankton and an ideal Case 2 water as a suspension of non-living materials with zero concentration of pigments. Thus, Case 1 water contains a high concentration of non-living materials with zero concentration of phytoplankton compared to that of other particles, and the pigments play a major role in actual absorption. In contrast, the inorganic particles are dominant in Case 2 waters, and pigment absorption is of comparatively minor importance. In accord with that definition, PRE waters with chl-a below 2 mg m\(^{-3}\) were quite close to Case 2 where NAP is a main component of suspended matter. As chl-a was above 2 mg m\(^{-3}\), TSS and chl-a correlate closely (\(R^2 = 0.7\)). In these waters, both NAP and phytoplankton govern optical properties. In this range of chl-a concentration, PRE waters are neither Case 1 nor Case 2 waters.

The reflectance spectra (figure 3(A)) were quite similar in magnitude and shape to the reflectance spectra of productive waters with very well pronounced spectral features in the red and NIR ranges of the spectrum, i.e. troughs due to chl-a absorption near 670 nm and peaks around 690–700 nm (Gitelson 1992, Lee et al 1998, Dall’Olmo and Gitelson 2005a, 2005b). The reciprocal of reflectance (figure 3(B)) revealed pronounced troughs in the green range (around 570 nm) due to minimal absorption by phytoplankton pigments, peaks near 670 nm (chl-a absorption), and a minimum in the range around 700 nm caused by a minimal combined absorption of algae and water (Vasilkov and Kopelevich 1982, Gitelson 1992, Gower et al 1999). This spectral feature is specific for turbid productive waters. The peak position shifted towards a longer wavelength from 686 to about 696 nm as the chl-a concentration increased from 1 to 11 mg m\(^{-3}\) (figure 4).

The high correlation between chl-a and TSS and the pronounced spectral features in the red and NIR range of the spectrum, typical for productive turbid waters, are interesting features of the waters studied. On this basis, the performance of the models used to retrieve chl-a concentrations, developed for both Case 1 and Case 2 waters was tested. The MBR calculated in the spectral bands of MODIS (O’Reilly et al 1998) showed a very close relationship (\(R^2 > 0.93\)) with the chl-a concentration (figure 5(A)). The NIR-to-red ratio (equation (2)), calculated in the spectral bands of MODIS centred at 750 and 665 nm, was closely related to a chl-a concentration below 6 mg m\(^{-3}\) and then levelled off and was almost insensitive to further increase in chl-a concentration (figure 5(B)).

The reciprocal reflectance at 675 nm, \(\rho^{-1} \propto (a + b_k)/b_o\), was weakly related to chl-a (figure 6(A)) showing that, in addition to chl-a, it was strongly affected also by variation in the TSS concentration (figure 6(B)). In the waters studied, as it was a case for less complex ocean waters (Morel and Prieur 1977), there appears to be no spectral band in which the influence of a single absorbing component (i.e. chl-a) can be

---

**Table 1a.** Spectral bands of MODIS used.

| Band number | Bandwidth (nm) |
|-------------|----------------|
| 9           | 438–448        |
| 10          | 483–493        |
| 11          | 526–536        |
| 12          | 546–556        |
| 13          | 662–672        |
| 14          | 673–683        |
| 15          | 743–753        |

**Table 1b.** Spectral bands of MERIS used.

| Band number | Bandwidth (nm) |
|-------------|----------------|
| 7           | 660–670        |
| 8           | 677.5–685      |
| 9           | 700–710        |
| 10          | 750–757        |

---

**Figure 2.** Relationship between TSS and chl-a concentrations. The concentrations of these constituents correlated very closely with \(R^2\) above 0.88.
Figure 3. (A) Reflectance and (B) reciprocal of reflectance spectra.

Figure 4. Peak position plotted versus chl-a concentration.

Figure 5. (A) Maximum band ratio (MBR) calculated in spectral bands of MODIS and (B) NIR-to-red ratio (equation (2)), calculated in MODIS bands centred at 750 and 665 nm, plotted versus chl-a concentration. MBR has a close relationship ($R^2 > 0.93$) with chl-a concentration. The NIR-to-red ratio also related closely to concentration of chl-a below 6 mg m$^{-3}$ and then levelled off and was almost insensitive to further increase in chl-a concentration.

completely isolated. Subtraction of the effect of backscattering by suspended matter (Dall’Olmo et al 2003, Dall’Olmo and Gitelson 2005a, 2005b) was needed.

Using an optimization procedure for the three-band model in equation (4), the optimal spectral regions for $\lambda_1$, $\lambda_2$, and $\lambda_3$ were found. The optimization procedure was based on minimizing the root mean square error (RMSE) of chl-a estimates (Dall’Olmo and Gitelson 2005a, 2005b, Gitelson et al 2008). This was achieved by optimizing the wavelengths used in the model (equation (4)) by initially setting $\lambda_1 = 665$ nm (red chl-a absorption maximum) and $\lambda_3 = 730$ nm (reflectance at this wavelength is not affected by pigment absorption and is governed by scattering from all particular matters). Then the model $[\rho^{-1}(665) - \rho^{-1}(\lambda_2)] \times \rho(\lambda_3)$ was regressed against the measured chl-a concentration for values of $\lambda_2$ between 400 and 800 nm. The minimal RMSE of chl-a estimation was found around 700 nm (figure 7(B)).

In the second iteration, $\lambda_2$ was set to 700 nm and then the model $[\rho^{-1}(665) - \rho^{-1}(700)] \times \rho(\lambda_3)$ was regressed against the measured chl-a concentrations for values of $\lambda_3$ between 400 and 800 nm. The minimal RMSE was found in a wide range around 730–745 nm (figure 7(C)). In the final iteration, $\lambda_3$ was set to 730 nm and $\lambda_1$ was optimized by regressing the model $[\rho^{-1}(\lambda_1) - \rho^{-1}(700)] \times \rho(730)$ against the measured concentrations of chl-a for values of $\lambda_1$ between 400 and 800 nm. The minimal RMSE was found in the range around 665 nm (figure 7(A)).

Thus, the model for chl-a estimation was optimized in the form:

$$\text{chl-a} = 34.811[(\rho^{-1}(665) - \rho^{-1}(700)] \times \rho(730)] + 2.8.$$ (7)
Figure 6. The reciprocal reflectance at 675 nm, $\rho_{-670}^{-1} \propto (a + b_b)/b_b$, plotted versus (A) chl-a concentrations and (B) TSS concentrations. $\rho_{-670}$ weakly related to chl-a; it is affected by variation in TSS concentration.

As a result, the model in equation (7) with spectral bands of 665, 700, and 730 nm was closely linearly related to chl-a concentrations, with $R^2$ reaching 0.96 and an RMSE of the chl-a estimation of below 0.87 mg m$^{-3}$ (figure 8). It is important to note that all of the optimal spectral regions found for this dataset are in line with previous studies of turbid productive Case 2 waters (Dall’Olmo and Gitelson 2005a, 2005b, 2006, Gitelson et al 2008, 2009, 2011, Moses et al 2009a, 2009b).

The optimization procedure (figures 7(A)–(C)) showed that an RMSE below 1 mg m$^{-3}$ may be achieved in spectral bands with more than 10 nm width and that these optimal bands are even wider than the MERIS bands 7, 9, and 10: 660–670 nm, 700–710 nm, and 750–757 nm, respectively. Thus, MERIS can be used to monitor the chl-a in these waters. It is also worth noting that the optimal spectral bands of the three-band model in equation (4) for $\lambda_2$ and $\lambda_3$ coincide in the range 690–712 nm (figure 9). This means that for the waters studied, the three-band model can be replaced by the two-band model (equation (3)): $\rho(\lambda_3)/\rho(\lambda_1)$ with $\lambda_1$ around 670 nm and $\lambda_3$ around 705 nm.

The two-band model (equation (3)) with MERIS spectral bands centred at $\lambda_1 = 665$ nm and $\lambda_2$ at 708 nm, and $\lambda_3 = 753$ nm (figure 10(B)) and the two-band model with MERIS bands (figure 10(A)) were good proxies for chl-a explaining more than 93% of the chl-a variation. The RMSE of the chl-a estimation using model equation (5) (Le et al 2009) with narrow bands and equation (6) (Yang et al 2010) with MERIS bands were 1.2 mg m$^{-3}$ and 1.24 mg m$^{-3}$, respectively, and thus did not bring about any improvement of the chl-a estimation.

Importantly, in all NIR–red models tested with MERIS spectral bands (equations (3), (4), and (6)), the replacement of the spectral band centred at 665 nm by the MERIS bands...
Figure 8. The three-band model (equation (4)) with spectral bands 665, 700, and 730 nm closely linearly related to chl-a with $R^2$ reached 0.96 and a RMSE of chl-a estimation below 0.87 mg m$^{-3}$.

Figure 9. Root mean square error of chl-a estimation by the three-band model plotted as a function of wavelength. The optimal spectral bands of the three-band model for $\lambda_2$ and $\lambda_3$ coincide in the range from 690 to 712 nm.

centred at 681.5 nm led to a significant increase of error of chl-a estimation (more than 30% in the models of equations (3) and (4) and more than 60% for the model in equation (6)). This finding is in line with the sensitivity analysis of Dall’Olmo and Gitelson (2006) who suggested the use of $\lambda_1$ in the range of 660–670 nm. They found that a higher accuracy in the chl-a estimation will be obtained when $\lambda_1$ is shifted from the region of maximal chl-a absorption (around 675–680 nm in situ) to a spectral region where the algorithms are less sensitive to variations in the bio-optical parameters (phytoplankton specific absorption coefficient, quantum yield of fluorescence, and reflectance uncertainties). Remarkably, the optimal spectral bands for NIR–red models coincide with the spectral bands of the MERIS system, thus allowing the MERIS data to be used for monitoring chl-a in waters with different trophic status.

4. Conclusions

The results obtained in this study provide evidence that the maximal band ratio (MBR), which uses blue and green spectral bands, and models using red and NIR bands are able to accurately estimate chl-a concentrations in the estuary waters of the Pearl River. With an accurate atmospheric correction of the satellite data, the MBR and the NIR–red models can be reliably applied to MODIS and MERIS data to achieve accurate estimation of chl-a concentrations.

The bio-optical signal, in both coastal and off-shore environments, is variable with respect to both the space and the time. Thus, the optical characteristics of waters may be different from those presented in our limited data set. However, the dynamic range of chl-a and TSS concentration was wide and typical for PRE waters. Thus, the algorithms presented likely would be reliable for estimating chl-a concentration in this area. The results suggest that the blue–green models would probably be accurate in areas nearer to the sea (figure 5(A)). However, in inland areas, which are turbid and productive, these spectral regions are of limited value in retrieving chl-a concentration. In these waters, the concentrations of non-algal particles and CDOM are uncorrelated with phytoplankton concentration, and they have strong overlapping absorption features in the blue spectral region, which makes the blue reflectance an unreliable indicator of the chl-a concentration (e.g. Gitelson 1992, Gons 1999, Ruddick et al 2001). With
increase in chl-a, the accuracy of these models sharply decreases. Thus, the NIR–red models that use the information in the red and the NIR regions are reliable and more accurate for estimating chl-a concentration in turbid productive waters, as the absorption effects of non-algal particles and CDOM largely weaken in those portions of the electromagnetic spectrum.

The choice of the best algorithm for the waters studied has yet to be made. Ultimately, it will depend on testing the performance of the blue–green and NIR–red models using MODIS and MERIS satellite data. The spatial resolution of 300 m gives the MERIS data a significant advantage especially for estuarine areas. The project is progressing to apply the algorithms in wider areas using MERIS and MODIS satellite data.

Acknowledgments

The authors are extremely grateful to Heying Shi, Shilin Tang, Dazhao Liu, and Fenfen Liu from the South China Sea Institute of Oceanology (SCSIO) under the Chinese Academy of Sciences (CAS), and Guiwu Wang, Yufei Wang, Hongyan Xi, and Su Yan from the Chinese University of Hong Kong (CUHK) for their help in data collection from the field water sampling and spectral reflectance measurements. The authors would also like to thank the two anonymous reviewers who gave helpful and critical comments to improve the original manuscript. The research is jointly supported by the CUHK Direct Grants (4450188 and 2020928), GRF (CUHK454909 and CUHK459210), and ITF (ITS/058/09FP).

References

Bao Y and Ren J 2005 Numerical simulation of high resolution on the phenomenon of saline stratification in LinDinYang J. Hydrodyn., 20 689–93
Chen X, Yuan Z, Li Y and Wei Y 2005 Spatial and temporal dynamics of suspended sediment concentration in the Pearl River Estuary based on remote sensing Geomat. Inform. Sci. Wuhan University 8 677–81
Dall’Omo G and Gitelson A A 2005a Effect of bio-optical parameter variability on the remote estimation of chlorophyll-a concentration in turbid productive waters: experimental results Appl. Opt. 44 412–22
Dall’Olmo G and Gitelson A A 2005b Appl. Opt. 44 3342 (erratum)
Dall’Olmo G and Gitelson A A 2006 Effect of bio-optical parameter variability and uncertainties in reflectance measurements on the remote estimation of chlorophyll-a concentration in turbid productive waters: modeling results Appl. Opt. 45 3577–92
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 1038
Dall’Olmo G, Gitelson A A, Rundquist D C, Leavitt B, Barrow T and Holz J C 2005 Assessing the potential of SeaWiFS and MODIS for estimating chlorophyll concentration in turbid productive waters using red and near-infrared bands Remote Sens. Environ. 96 176–87
Dekker A 1993 Detection of the optical water quality parameters for eutrophic waters by high resolution remote sensing PhD Thesis Free University, Amsterdam, The Netherlands
Gitelson A and Kondrat’ev K 1991 Optical models of Mesotrophic and Eutrophic Waters Int. J. Remote Sens. 12 373–85
Gitelson A, Keydan G and Shishkin V 1985 Inland waters quality assessment from satellite data in visible range of the spectrum Sov. J. Remote Sens. 6 28–36
Gitelson A, Nikanorov A M, Sabo G and Szilagyi F 1986 Etude de la qualité des eaux de surface par teledetection IAHS Publications 157 111–21
Gitelson A A 1992 The peak near 700 nm on reflectance spectra of algae and water: relationships of its magnitude and position with chlorophyll concentration Int. J. Remote Sens. 13 3367–73
Gitelson 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
Gitelson A A, Griz U and Merzlyak M N 2003 Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves J. Plant Physiol. 160 271–82
Gitelson 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
Gitelson A A, Gurlin D, Moses W J and Yacobi Y Z 2011 Advances in Environmental Remote Sensing: Sensors, Algorithms and Applications ed Q Weng (Boca Raton, FL: CRC Press) pp 449–78, chapter 18 (Remote Estimation of Chlorophyll-a Concentration in Inland, Estuarine, and Coastal Waters)
Gitelson A A, Schalles J F and Hladik C M 2007 Remote chlorophyll-a retrieval in turbid, productive estuaries: Chesapeake Bay case study Remote Sens. Environ. 109 464–72
Gons H J 1999 Optical teledetection of chlorophyll a in turbid inland waters Environ. Sci. Technol. 33 1127–32
Gordon H and Morel A 1983 Remote assessment of ocean color for interpretation of satellite visible imagery. A review Lecture Notes on Coastal and Estuarine Studies vol 4, ed R T Barber, C N K Mooers, M J Bowman and B Zeitzschel (New York: Springer) p 7
Gordon H R, Brown O B and Jacobs M M 1975 Computed relationships between the inherent and apparent optical properties of a flat homogeneous ocean Appl. Opt. 14 417–27
Gower J F R, Doerffer R and Borstad G A 1999 Interpretation of the 685 nm peak in water-leaving radiance spectra in terms of fluorescence, absorption and scattering, and its observation by MERIS Int. J. Remote Sens. 20 1771–86
Hoge E F, Wright C W and Swift R N 1987 Radiance ratio algorithm wavelengths for remote oceanic chlorophyll determination Appl. Opt. 26 2082–94
Kirk J T O 1994 Light and Photosynthesis in Aquatic Ecosystems (Cambridge: Cambridge University Press) p 509
Le C, Li Y, Zha Y, Sun D, Huang C and Lu H 2009 A four-band semi-analytical model for estimating chlorophyll-a in highly turbid lakes: the case of Taihu Lake, China Remote Sens. Environ. 113 1175–82
Lee Z P, Carder K L, Moleby C D, Steward R G and Patch J S 1998 Hyperspectral remote sensing for shallow waters. I. A semianalytical model Appl. Opt. 37 6329–38
Li X 1992 A united equation for remote sensing quantitative analysis of suspended sediment and its application at Zhujiang River estuary J. Remote Sens. 7 106–14
Liu X, Deng R and Peng X 2005 An integrated model for quantitative remote sensing measurement of suspended sediment and its application in the Pearl River estuary Acta Sci. Nat. Univ. Sunyatseni 44 109–13
Moleby C D 1994 Light and Water: Radiative Transfer in Natural Waters (San Diego, CA: Academic) p 592
Morel A and Prieur L 1977 Analysis of variations in ocean color Limnol. Oceanogr. 22 709–22
Moses W J, Gitelson A A, Berdnikov S and Povazhnyy V 2009a Estimation of chlorophyll-a concentration in case II waters using MODIS and MERIS data—successes and challenges Environ. Res. Lett. 4 045005
Moses W J, Gitelson A A, Berdnikov S and Povazhnyy V 2009b Satellite estimation of chlorophyll-a concentration using the red
and NIR bands of MERIS—the Azov sea case study IEEE Geosci. Remote Sens. Lett. 6 845–9
Mueller J L, Fargion G S and McClain C R (ed) 2003 Ocean Optics Protocols for Satellite Ocean Color Sensor Validation, Revision 4 vol 1–4 (Greenbelt, MD: Goddard Space Flight Center)
Oki K and Yasuoka Y 2002 Estimation of chlorophyll concentration in lakes and inland seas with a field spectroradiometer above the water surface Appl. Opt. 41 6463–9
O’Reilly J E, Maritorena S, Mitchell B G, Siegel D A, Carder K L, Garver S A, Kahrut M and McClain C 1998 Ocean color chlorophyll algorithms for SeaWiFS J. Geophys. Res.—Oceans 103 24937–53
Pierson D and Strömbeck N 2000 A modelling approach to evaluate preliminary remote sensing algorithms: use of water quality data from Swedish great lakes Geophysica 36 177–202
Pulliainen J, Kallio K, Eloheimo K, Koponen S, Servomaa H, Hannonen T, Tauriainen S and Hallikainen M 2001 A semi-operative approach to lake water quality retrieval from remote sensing data Sci. Total Environ. 268 79–93
Ruddick K G, Gons H J, Rijkeboer M and Tilstone G 2001 Optical remote sensing of chlorophyll a in case 2 waters by use of an adaptive two-band algorithm with optimal error properties Appl. Opt. 40 3575–85
Stumpf R P and Tyler M A 1988 Satellite detection of bloom and pigment distributions in estuaries Remote Sens. Environ. 24 385–404
Vasilkov A and Kopelevich O 1982 Reasons for the appearance of the maximum near 700 nm in the radiance spectrum emitted by the ocean layer Oceanology 22 697–701
Yacobi Y Z, Gitelson A A and Mayo M 1995 Remote sensing of chlorophyll in Lake Kinneret using high spectral resolution radiometer and Landsat TM: spectral features of reflectance and algorithm development J. Plankton Res. 17 2155–73
Yang W, Matsushita B, Chen J, Fukushima T and Ma R 2010 An enhanced three-band index for estimating chlorophyll-a in turbid case-II waters: case studies of Lake Kasumigaura, Japan, and Lake Dianchi, China IEEE Geosci. Remote Sens. Lett. 7 655–9