Approximate bottom contribution to remote sensing reflectance in Taihu Lake, China

Ronghua Ma a, Hongtao Duan a,⁎, Qinhuo Liu b, Steven Arthur Loiselle c

a State Key Laboratory of Lake Science and Environment, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing, PO BOX 210008, P. R. China
b State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, Beijing, PO BOX 10008, P. R. China
c University of Siena, Siena, Italy

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A B S T R A C T

Remote sensing is a fundamental tool for the analysis of spatial and temporal trends in lake ecosystems. A major challenge in using these approaches is determining the possible influence of reflectance from submerged vegetation or the lake bottom. In the present study, we examine the water leaving radiance measured in a large number of sites in Taihu Lake, a large shallow lake in southeast China. Due to the high concentrations of suspended sediment and phytoplankton biomass, a majority of the lake can be considered optically deep (i.e. bottom reflectance could be ignored). However, optically shallow waters were present in the shallow bays on the eastern side of the lake. In these areas, submerged vegetation was present. To explore the contribution of the lake bottom and submerged vegetation on remotely sensed reflectance, we compared two modeling approaches (Hydrolight and the LEE). The results show that differences in optical and physical characteristics of the lake bottom strongly influence the spectral characteristics of the measured reflectance. The resulting impact on the estimate of chlorophyll-a concentrations was tested using datasets with and without sites where bottom effects may occur. A significant improvement in the predictive capacity of the reflectance based estimated of phytoplankton biomass was made when areas with bottom influences were removed from the calibration procedure.

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Introduction

In recent decades, remote sensing has emerged as an important branch of oceanography with many developments in estimating ocean color and the concentration of optically active constituents (e.g. suspended sediments, chlorophyll, etc.,) (Mueller et al., 2003; Bricaud et al., 1999; Gordon, 1995; Carder et al., 1991; Viollier et al., 1980; Dekker, 1993). In more recent years, increased attention has been directed towards remote sensing applications in limnology, especially for lakes strongly impacted by human activities. There are many challenges to developing these retrieval algorithms, including the accurate measurement of irradiance reflectance.

Irradiance reflectance is the sum of upward reflected irradiance from the water itself and the bottom. In optically deep waters, e.g., oceans, the influence of the bottom can be ignored. However, in optically shallow waters, reflected irradiance from the lake floor can be significant. The contribution of bottom reflectance to water leaving radiance (measured by a remote sensor) depends on the water depth, the optical properties of the water column and the optical properties of the bottom (Lodhi and Rundquist, 2001).

Several studies have investigated bottom reflectance properties and effects. Voss et al. (2003) showed that the upwelling radiance distribution over turtlegrass was near-Lambertian at a wavelength of 440 nm. Hojerslev (1977) determined that lake bottom effects on the upwelling spectral signal can be considered insignificant when water depth is three times Secchi disk depth. Mueller and Austin (1995) assumed that the bottom influence may be ignored when water depth is 2.5 times greater than the attenuation length.

For flat and homogenous bottoms with Lambertian reflectance, irradiance reflectance (R) can be estimated from the Bidirectional Reflectance Distribution Function (BRDF) (Gordon and Brown, 1974; Mobley and Sundman, 2003). Maritorena et al. (1994) derived a simple expression of irradiance reflectance using the radiative transfer equation. Lee et al. (1994) included Raman scattering of water in their equation of reflectance. Later, Lee et al. (1998) developed an equation for the subsurface upwelling signal which included contributions due to the water and the bottom; Albert and Mobely (2003) gave a more general, but more complex expression that considers a viewing angle just below the water surface. Lee et al. (1999) then developed a semianalytical model to estimate the subsurface reflectance in shallow waters which accounted for solar zenith angle; this was then refined by using HydroLight simulations (Becker et al., 2009).

Taihu Lake, a large (2427.8 km²) shallow (mean depth 1.9 m; maximum depth max. 2.6 m) lake, is the third largest fresh-water lake...
in China. It is located in the Yangtze Delta, in eastern China and has a watershed with a high population density (Fig. 1). Eutrophication has intensified in recent years and algal blooms increased, covering large areas of the lake since the 1980s (Duan et al., 2009). The inherent optical properties (IOPs) of Taihu Lake are determined by phytoplankton (chlorophyll-a, CHL), suspended particulate matter (SPM), and chromophoric dissolved organic matter (CDOM). Therefore, absorption and backscattering are controlled by the concentrations and optical properties of phytoplankton (index \( \text{ph} \)), non-algal particulate matter (index \( \text{d} \)), pure water (index \( \text{w} \)), and absorption due to CDOM (index \( \text{g} \)). The total absorption \( a \) is the sum of absorption of each of these components (Jerlov, 1976; Prieur and Sathyendranath, 1981).

In some areas of Taihu Lake, e.g. the southeast, waters can be relatively clear and optical properties of both the lake bottom and water column may influence the upwelling irradiance. Although numerous studies using remote sensing have been conducted in Taihu Lake (Ma et al., 2006a, 2006b; Sun et al., 2009; Zhang et al., 2009), none have measured the bottom contribution to remote sensing reflectance. Such information is necessary to improve the algorithms used to monitor changes in Taihu Lake waters.

In the present study, we explore the contribution of bottom reflectance on the surface upwelling irradiance of Taihu Lake. We used measurements and observations obtained in an extensive lake survey conducted in October 2004. We examine the results of both the Hydrolight radiative transfer model and the LEE model and compare them to measured reflectance to explore the contribution of reflected bottom irradiance to remote sensing reflectance. We compare the estimation of chlorophyll-a from reflectance measurements by excluding areas where bottom effects may be important to using the full lake dataset, to examine how an improved understanding of these impact influences our ability to observe spatial trends in this important lake.

**Methods**

**Field and laboratory methods**

From October 18–29, 2004, we measured IOPs at 67 stations throughout the lake (Fig. 2); two sites (sites 17 and 18) were excluded from subsequent analyses because of faulty measurements of remote sensing reflectance. Field measurements included water depth, Secchi disk transparency, wind speed and direction, water temperature and water-leaving radiance, backscattering and bottom spectra. Water samples were collected in the first 0.30 m of the water column, using a pre-rinsed 2-liter polyethylene water-bottle. These samples were collected in the afternoon and kept in the dark at 4 °C until analyses for estimating the concentrations of chlorophyll-a, SPM, and DOC and their related absorption i.e., phytoplankton pigment absorption, non-algal particulate absorption and CDOM absorption.

Water transparency was measured with a Secchi disk at the shaded side of the boat while water-leaving radiance was measured in situ using a dual channel FieldSpec 931 spectrometer (ASD Ltd., USA) following NASA protocols (Mueller et al., 2003). The backscattering coefficient was measured using a HydroScat-6 Spectral Backscattering Sensor (HS-6, HOBI Lab Inc.) at six wavelengths, respectively, centered at 442, 488, 532, 589, 676 and 852 nm, following HOBI-labs Inc. (2003); the instrument was calibrated for the dark offset and gain ratios prior to its use. After the field sampling, a sigma correction was performed to improve the accuracy of backscattering measurements; this was needed because some light was lost due to the water's attenuation resulting in an underestimate of scattering, i.e., when light traveled from the sensor to the scattering site and back. For very clear waters, the correction factor is insignificant, but as turbidity increases so does the underestimate of scattering; therefore an accurate backscattering probability \( \tilde{b}_b \) (the ratio of backscattering coefficient to scattering coefficient) was used.

![Fig. 1. The location of the Taihu Lake in China.](image1)

![Fig. 2. Locations of study sites and optical regions defined by whether or not water-leaving radiance is affected by the lake bottom.](image2)
The lake floor was sampled with a bottom grab after the water column measurements had been completed. For mud-covered or bottoms with sparse vegetation, the sediment sample was placed in a tray and the allowed to settle for 20 min, after which most of the overlying water was decanted and the sediment surface smoothed. A vegetation sample was placed in the tray with 0.01 m of overlaying lake water. 

GF/F 25 mm diameter, 0.70 

Chlorophyll-a (CCHL) was extracted using 90% ethanol and measured with a UV2401 spectrophotometer following standard methods. SPM concentrations (CSPM) were determined gravimetrically from samples collected on the pre-combusted and pre-weighted 47 mm diameter GF/F filters and dried at 95 °C overnight; SPM was differentiated into an inorganic (Cinorg) and organic fractions (Corg) by combusting the suspended substance filters at 550 °C for three hours. Total particulate matter absorption, ap(λ), and non-algal particulate absorption, an(λ) where measured by the quantitative filter technique (QFT); phytoplankton pigment absorption, ap(λ), was calculated by subtracting an(λ) from ap(λ). CDOM absorption, ap(λ), was measured specrophotometrically in a 10-cm cuvette using a UV-2401 spectrophotometer after filtering lake water with a Whatman GF/F filter; distilled water was used as the reference. More information on methods can be found in Ma et al. (2006a, 2006b).

Simulation and modeling methods

Remote sensing \( r_{rs} \) reflectance for turbid waters can be described by Eq. (1) developed by (Dekker et al., 1997).

\[ r_{rs}(\lambda) = \frac{f}{Q} \frac{b_{s}(\lambda)}{a(\lambda) + b_{s}(\lambda)} \]  

(1)

where \( r_{rs} \) is remote sensing reflectance just beneath the water surface and \( R_{rs} \) the remote sensing reflectance above the water surface; \( f \) is the water-to-air diffuse transmittance and \( Q \) refractive index of water, both of which generally are considered to be constant in the same water; \( f = 0.975 - 0.629 \mu_{b} \) after Kirk (1994); and \( \mu_{b} \) is the mean cosine of angles the photons make with the vertical just below the surface after refraction at the surface. \( Q \) is the distribution parameter of the light field. Gordon (1989) showed that the ratio of \( f/Q \) varied less with solar elevation than the factors \( f \) and \( Q \) themselves. Because the ratios of \( f/Q \) and \( t/n^2 \) are usually similar for most waters, we substitute \( f' \) for \( (f/Q)/(t/n^2) \). The total absorption coefficient is \( a(\lambda) \), a sum of contributions due to pure water, CDOM, phytoplankton and non-algal particulate:

\[ a(\lambda) = a_{w}(\lambda) + a_{p}(\lambda) + a_{pg}(\lambda) + a_{n}(\lambda) \]  

(2)

where the absorption coefficient of pure water, \( a_{w}(\lambda) \), comes from Pope and Fry (1997) in the range of 380 to 700 nm. The total backscattering coefficient is \( b_{s} \), a sum of contributions due to pure water \( b_{w} \), and due to suspended particulate matter \( b_{sp} \):

\[ b_{s}(\lambda) = b_{sw}(\lambda) + b_{sp}(\lambda) \]  

(3)

where \( b_{sw} \) is also known (Morel, 1974); \( b_{sp} \) a sum of contributions due to phytoplankton and non-algal suspended particulate.

Since in optically shallow waters, remote sensing reflectance comes from contributions from both the water column and the lake bottom, (Lee et al., 1999)

\[ r_{rs} = r_{rs}^{up} + r_{rs}^{bp} \exp \left\{ \left[ \frac{1}{\cos(\theta_{u})} + D_{B}' \right] n H \right\} \]  

(4)

\[ + \frac{1}{\pi} \exp \left\{ \left[ \frac{1}{\cos(\theta_{u})} + D_{B}' \right] n H \right\} \]

where \( r_{rs}^{up} \) is the subsurface reflectance from the water column only; \( r_{rs}^{bp} \) is the subsurface reflectance from the bottom only; \( r_{rs}^{bp} \) is the subsurface reflectance for the optically deep waters or only from water column, coming from Eq. (1) \( (r_{rs}^{bp}(\lambda)) \); \( \theta_{u} \) is the subsurface solar zenith angle, \( p \) is the bottom albedo, \( H \) is the lake depth, \( \kappa \) the attenuation coefficient, \( D_{B}' \) and \( D_{B}\) are distribution functions of \( a \) and \( b_{p} \) from water column and bottom, respectively. More information can be found in Appendix A.

Simulations were done with HydroLight software at all sites in the optically shallow waters; however, only data from station 57 (1.80 m deep) with a minimum of suspended particulate matter concentration (3.10 mg/l), and station 43 (1.30 m deep) with a maximum of suspended particulate matter concentration (23.24 mg/l) are reported here. Reflectance \( R_{rs}^{s} \) coming from the optically shallow waters with the bottom reflectance measured \( in situ \) was simulated first. Next we progressively raised the height of the simulated bottom vegetation; for station 57 at 0.10 m, 0.50 m, 0.90 m, 1.30 m, and 1.70 m above the bottom while for station 43 simulations were performed at 0.10 m, 0.30 m, 0.60 m and 1.20 m from the bottom. Next we simulated the reflectance \( R_{rs}^{s} \) under the assumption that the water was optically deep using the measured water quality and inherent optical properties. Thirdly, reflectance from the HydroLight radiative transfer model and the LEE model were compared with that measured \( in situ \) in order to estimate bottom contribution to reflectance. Simulations using the HydroLight and LEE models were run under the assumptions of an infinitely horizontal bottom with Lambert properties and homogenous water quality. Finally, we use a three waveband algorithm for estimating chlorophyll-a concentrations to examine the difference in the spatial distribution of estimated phytoplankton biomass, in one case using the entire dataset and in the other by using the a reduced dataset, without sites where bottom effects may occur.

Results and discussion

Optically speaking, Taihu Lake can be divided into three zones (Fig. 2), i.e., bottom-influenced zone (optically shallow), possibly bottom-influenced zone and non-bottom-influenced (optically deep) zones (Ma et al., 2006a). Most of the lake is optically deep while the optically shallow area is limited to the protected bays to the east. Optically deep waters (Table 1) had the highest chlorophyll and suspended sediment concentrations and the lowest Secchi disk transparency. Optically shallow waters are shown in Table 2. The average bottom reflectance (Fig. 3) increased gradually with wavelength for mud-covered bottoms, whereas reflectance increased markedly at 675 nm for vegetated bottoms. At lower wavelengths, reflectance was greatest for mud bottoms.

Hydrolight simulation

At site 57 (East Taihu Bay), the deep station with a muddy bottom and sparse vegetation, \( R_{rs}^{s} \) (measured remote sensing reflectance) was greater than \( R_{rs}^{om} \) (simulated remote sensing reflectance using the HydroLight model) at most wavelengths (Fig. 4). For areas with the vegetation growing close to the water surface, the simulation showed a decrease in reflectance in the blue and green (\( \lambda < 590 \) nm) and an increase in the red and near-infrared. In all simulations, \( R_{rs}^{om} \) in
particulate matter, vegetation height increased towards the surface in most wavelengths, maximum of 0.0034 (65.2% of vegetation (thin black line). (thick black line), mud-covered bottoms (thick dash line) and bottoms with dense vegetation (thin black line),

optically deep waters was greater than that in optically shallow waters with bottom vegetation for wavelengths below 590 nm. On the other hand, $R_{rs}$ in optically deep waters was less than that for optically shallow waters with a mud bottom throughout the visible and near infrared.

$R_{rs}$ was greater for shallow mud bottoms than for vegetated bottoms or bottoms with a mixture of vegetation and mud. As the vegetation approached the surface, $R_{rs}$ decreased gradually in the range of 380 to 710 nm. When bottom vegetation reached 0.40 m beneath the surface, $R_{rs}$ began to increase at wavelengths greater than 710 nm and show spectral characteristics similar to that of terrestrial vegetation; this pattern continued as vegetation height approaches the surface (Fig. 5).

In situ measured reflectance, $R_{sm}$, was measured in two locations at the shallow site 43, which is characterized by high concentrations of suspended sediments. One location had bottom vegetation height with a height of about 0.50 m while the other had a height of about 0.90 m (Fig. 4).

At the 0.90 m high patch, $R_{sm}$ was greater than $R_{rs}$, from a maximum of 0.0034 (65.2% of $R_{rs}$) at 381 nm to a minimum of 0.0001 (0.6% of $R_{rs}$) at 683 nm. From 583 nm to 727 nm, the simulated and measured values were very close, with a maximum difference of 0.0017 (10.7% of $R_{rs}$) at 605 nm and an average difference of 0.0007 (5.3% of $R_{rs}$). Differences gradually increased in the 728 to 750 nm range and exceeded 20% of $R_{rs}$. Differences were reduced as vegetation height increased towards the surface in most wavelengths, i.e., from 7.7% of $R_{sm}$ with zero height to 19.4% of $R_{rs}$ for 0.9 m vegetation, considering all wavelengths. The maximum at the 0.5 m high patch was 0.0033 (12.2% of $R_{rs}$) at 575 nm, and the minimum is zero at about 522 and 668 nm. Therefore, the Hydrolight simulation produced larger errors as bottom vegetation approaches the surface (Fig. 4).

LEEP model estimation

Using the LEE approach to model remote sensing reflectance, $R_{sm}$ decreased gradually with increasing vegetation height (Figs. 6 and 7) and was greater for more turbid water (site 43). $R_{sm}$ is greater in optically deep waters than in optically shallow waters with a bottom vegetation height of about 0.50 m. The relationship between modeled and measured reflectance ($R_{sm}/R_{rs}$) changed with different vegetation heights and different water clarity. For more turbid site 43, the $R_{sm}/R_{rs}$ ratio was closest to 1 for bottom vegetation with a height greater than 0.90 m. For the clearer water of site 57, the modeled reflectance closely followed the measured $R_{rs}$ with a vegetation height of 0.10 m, $R_{sm}/R_{rs}$ was ca. 0.5, 0.9, 1.3, 1.5 and 1.0 (Fig. 7).

Comparison between Hydrolight simulation and LEEP model estimation

A comparison between estimation approaches shows that the Hydrolight simulated reflectances were more representative of measured reflectance than the LEE modeled reflectance for site 43. The opposite is true for site 57 (Figs. 6 and 7). Simulated $R_{sm}$ was greater than the modeled $R_{sm}$, at both vegetation patches at site 43, while it was less than the modeled reflectance in site 57. Both methods overestimated reflectance in this clear water site.

Bottom contribution to upwelling measurements and simulation

The contribution of reflected irradiance from bottom vegetation depends on vegetation height, water quality and the wavelength considered. For relatively turbid yet optically shallow waters (e.g., site 43: Fig. 8a), remote sensing reflectance is due to reflectance from both water and bottom vegetation, with the latter increasing in importance as bottom vegetation approaches the water surface. The contribution from vegetation in the wavelength interval 442–676 nm range averaged, 6.7% (SD 6.5%) and 35.4% (SD 25.8%) of total reflectance for vegetation heights of 0.50 and 0.90 m height respectively. A

Table 1 Water quality measures for three zones in Taihu Lake, October 18–29, 2004 ($C_{\text{CCHL}}$ represents the concentration of chlorophyll-a, $C_{\text{CSPM}}$ represents the concentration of suspended particulate matter, $C_{\text{DOC}}$ represents the concentration of dissolved organic carbon, and SDT represents the transparency measured by the Secchi disk.).

| Site Location     | $C_{\text{CCHL}}$ (µg/l) | $C_{\text{CSPM}}$ (mg/l) | $C_{\text{DOC}}$ (mg/l) | SDT (cm) | Bottom depth (cm) | Bottom type                                                                
<table>
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</thead>
<tbody>
<tr>
<td>43 Xukou Bay</td>
<td>1.20</td>
<td>23.24</td>
<td>8.46</td>
<td>70</td>
<td>130</td>
<td>A mixture of mud and sparse vegetation with uneven height from 0.50 to 1.10 m</td>
</tr>
<tr>
<td>57 East Taihu Bay</td>
<td>4.87</td>
<td>23.24</td>
<td>8.46</td>
<td>70</td>
<td>130</td>
<td>A mixture of mud and sparse vegetation with uneven height from 0.50 to 1.10 m</td>
</tr>
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Fig. 3. Measured average reflectance spectrum for mud and sparsely vegetated bottoms (thick black line), mud-covered bottoms (thick dash line) and bottoms with dense vegetation (thin black line).
maximum of 15.4% and 67.5% occurred at 589 nm (green) for vegetation at 0.50 and 0.90 m respectively.

For optically shallow clearer waters (e.g., site 57), increased absorption due to vegetation occurred in the blue/green wavelengths while increased reflection occurred in the red wavelengths. For the more turbid waters of site 43, no increase in reflectance due to vegetation was observed at any wavelength.

The bottom contribution at any wavelength can be described by Eq. (5) as

$$\text{contri}(\lambda) = a \times H_1^3 + b \times H_1^2 + c \times H_1 + d$$

where \text{contri}(\lambda) is the bottom contribution (%) at a specific wavelength \(\lambda\); \(H_1\) is the distance from the water surface to the top of vegetation (m); \(a, b, c\) and \(d\) are constants derived from a least square regression. The mean bottom contribution to \(R_{rsr}\) for the five wavelengths were determined to be 12.0% (SD 10.3%), 16.9% (SD 14.5), 20.6% (SD 17.5), 38.6% (SD 32.5) and 59.0% (SD 50.4) for bottom vegetation with a height of 0.10, 0.50, 0.90, 1.30, 1.70 m. The maximum bottom contribution is 21.4%, 33.0%, 60.8%, and 97.6% for bottom vegetation with a height of 0.10, 0.50, 0.90, 1.30 and 1.70 m. The peak wavelength for the contribution of the bottom will vary with vegetation height. The bottom contribution is maximum at 532 nm when the vegetation reaches the half water column depth, then shifting to 488 nm for taller vegetation.

Bottom effects influence on chlorophyll-a estimations

The analysis of the temporal and spatial trends in the chlorophyll a concentrations in Taihu Lake is a key element in its study and long
term monitoring. To date, most algorithms have ignored the possible effects of reflected irradiance from the lake bottom. The preceding analysis shows that these effects could have an impact on the reflectance measured by remote sensors, thereby reducing our ability to monitor lake dynamics. To test this, we divided the reflectance data from the 65 measurement sites into two sets, those without possible bottom effects and those with possible bottom effects. We used three-band approach which has proven to be robust for turbid, productive waters (Dall’Olmo and Gitelson, 2006; Gitelson et al., 2008),

\[
[ \text{Rrs}(\lambda_1) - \text{Rrs}^{-1}(\lambda_2) ] \times \text{Rrs}(\lambda_3)
\]

where Rrs(\lambda_i), \lambda_1 falls in the region where Rrs(\lambda_1) is maximally sensitive to the phytoplankton pigments absorption (aph), \lambda_2 falls in the region where Rrs(\lambda_2) is minimally sensitive to aph(aph(\lambda_2) < aph (\lambda_1)), \lambda_3 is chosen to minimize backscattering effects by particulate matter. Absorption by other constituents at \lambda_2 is expected to be similar to that at \lambda_1. Considering the spectral distribution of chlorophyll-a and particulate backscattering; \lambda_1 should range between 660 nm and 690 nm, \lambda_2 should range from 670 to 710 nm, and \lambda_3 should be greater than 710 nm (Dall’Olmo and Gitelson, 2006).

The calibration of the three-band model was performed using an iteration algorithm in Matlab for the dataset of sites without bottom effects (47 sites). \lambda_1, \lambda_2 were found to be 666 nm and 688 nm, and \lambda_3 was 720 nm. The goodness of fit was found to be \(R^2 = 0.82\) (Fig. 9(b)). If our hypothesis is correct, this calibration should be better than if the entire dataset was used, including those sites where bottom effect occur. In fact, when using the full dataset (67 sites), the three optimal wavelengths changed (662 nm, 693 nm and 720 nm, respectively) and the fitting coefficient was reduced (\(R^2 = 0.79\)). This loss in accuracy can have profound impacts on the estimation of the spatial distribution of chlorophyll-a. In fact, significant differences occur between spatial distributions made with and without sites where

![Fig. 7. Comparison of measured and modeled reflectance at Site 57: a) measured (R_{rs}, No. 1), modeled by LEE (R_{rms}, No. 2), simulated by Hydrolight (R_{rss}, No. 3) for a patch with vegetation height of 0.10 m, b) modeled by LEE (R_{rms}, No. 4), simulated by Hydrolight (R_{rss}, No. 5) for a patch with a vegetation height of 0.90 m, c) modeled by LEE (R_{rms}, No. 6), simulated by Hydrolight (R_{rss}, No. 7) for a patch with a vegetation height of 1.70 m, and d) modeled by LEE (R_{rms}, No. 8), simulated by Hydrolight (R_{rss}, No. 9) for optically deep waters.](image)

![Fig. 8. The percentage of the measured total reflectance (R_{rs}) associated to bottom reflectance a) at Site 43 (column height 1.30 m) from vegetation with heights of 0.50 (crosses) and 0.90 m (triangles), and b) at Site 57 (column height 1.80 m) from vegetation with heights of 0.10 m (open squares), 0.50 m (crosses), 0.90 m (open triangles), 1.30 m (full squares), and 1.70 m (full triangles).](image)
bottom effects may occur (Fig. 10). In the former, east–west trends occur and optically shallow waters in the east show improbably high phytoplankton biomass. In the latter, the impacts of the highly polluted northern bays are clearer, with a clear trend of high biomass in the inner bays and lower in the open lake area.

Conclusions

In optically shallow waters, solar radiation can reach the lake bottom where it is reflected and contributes to the upwelling irradiance and water-leaving radiance measured by remote sensors. Clearly, the optical and physical properties of the lake bottom may influence the remotely sensed reflectance in optically shallow waters, specifically the spectral absorption, spectral reflectance and vegetation height (Lodhi and Rundquist, 2001). In Taihu Lake, the development of algorithms using only optically deep waters, where the influence of the lake bottom is minimum, allowed us to improve our ability to examine chlorophyll spatial dynamics. However, such manipulations can be complex, as the spatial distribution and community composition of aquatic vegetation can change inter- and intra-annually. Furthermore, the optical characteristics of the vegetation community will change over time, through modifications in the dominant plant species, vegetation height and spectral absorption of the individual species. However, if long term analyses of shallow lakes are to be made using remote sensors, the contribution of bottom effects on the water leaving radiance must be considered.

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![Fig. 9. Estimated reflectance and measured chlorophyll-a concentrations using a three-band model a) with the complete dataset and b) with the modified dataset where sites with bottom effects removed.](image)

![Fig. 10. Spatial distribution of estimated chlorophyll-a concentrations using a) the complete dataset and b) the modified dataset where sites with bottom effects removed. Interpolation made using Kriging. Dark grey areas in b) are considered optically shallow areas where reflectance includes bottom effects.](image)
References


