Chapter 2

The Empirical Models to Correct Water Column Effects for Optically Shallow Water

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Additional information is available at the end of the chapter

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Abstract

Seagrass as one of the blue carbon sinks plays an important role in environment, and it can be tracked remotely in the optically shallow water. Usually the signals of seagrass are weak which can be confused with the water column. The chapter will offer a model to simulate the propagation of light. The model can be used to improve the accuracy of seagrass mapping. Based on the in situ data, we found that the appropriate wavebands for seagrass mapping generally lie between 500–630 nm and 680–710 nm as well. In addition, a strong relationship between the reflectance value at 715 nm and LAI was found with a correlation coefficient of 0.99. The chapter provided an improved algorithm to retrieve bottom reflectance and map the bottom types. That would be meaningful for management and preservation of coastal marine resources.

Keywords: seagrass, optical correction model, Sanya Bay, remote sensing technique, optically shallow water

1. Introduction

Given the rapid change affecting coastal environments, it is a substantial challenge to manage and preserve the coastal marine resources. It is urgent to find an effective and quantitative tool to detect such change in the optically shallow water. The spatial resolution and precision of the traditional *in situ* surveys are not enough to detect subtle changes before they become catastrophic [1, 2]. Remote sensing technique developed rapidly and can provide high spatial and temporal resolution of the benthos. Optical properties in the optically shallow waters are relatively more complex than those in the optically deep water, so the application of remote sensing technique in optically shallow waters is still in its infant stage.

An important problem with remote sensing technique in the aquatic environment is the water column effect [3, 4]. In shallow water, radiance can be affected by phytoplankton, suspended organic and inorganic matter and dissolved organic substances [5, 6].

There are several methods to correct the water column effects. The single/quasi-single scattering theory is one of them to estimate the water column contribution. Morel and Gentili [7] defined the reflectance of the optically shallow waters by removing determinations of the albedo of the substrate covering the floor. The contribution of a finite substrate to the increase in reflectance was interpreted in terms of depth if the optical properties of the optically shallow water and the reflectance at null depth of the deep ocean near the object were known. The quasi-single scattering theory [8] suggests that bottom upwelling signals can be estimated as a sum of contributions from the water column and from the bottom. A semianalytical (SA) model for mapping bottom by using the remote sensing reflectance of shallow waters was developed and most commonly cited [9, 10]. Another algorithm to compensate for water column effects is that of Lyzenga [11–13]. This model was developed from two-flow irradiance transfer. Lyzenga exploited an intrinsic correlation between two color bands. This theory was utilized to generate a pseudodepth and pseudocolor band. The pseudodepth channel can theoretically be retrieved with appropriate ground truth information to estimate absolute depth. The total remote sensing reflectance values with respect to depth were linearized by removing an optically deep water value and taking the natural logarithm of the result. Removing a deep-water reflectance value from each pixel [14, 15] or applying the water optical properties [16] which are calculated from deep waters, were used to eliminate water column influence. However, there are several issues in these methods. Because these models utilized the hypothesis that energy traveling through a water column is not related to the substrate type and water depth. In fact the intensity of light in optically shallow water decreases exponentially with increasing depth, and changes from electromagnetic radiation. The error due to the process has reduced the accuracy of seagrass mapping and bottom classification. Based on these reasons, it is necessary to consider the water depth and the diffuse attenuation coefficient when removing the water column effects.

In this chapter, we will introduce an improved optical model of incoming solar radiation transfer. This model consumed the optically shallow water as multilayer water. This effective and improved method can be applied to research the relationship between reflectance and the LAI of seagrass.

2. The improved optically shallow water model

In this algorithm the optically shallow water is considered as a plane-parallel water body and segmented into an enormous number of homogenous layers to describe the optical properties of the optically water column. In this model, it is supposed an infinitely thin layer S of thickness Δz_i at depth z existed and can be measured downward from the sensor. The ith interval covers depths from z_i to z_{i+1}, with $\Delta z_i = z_{i+1} - z_i$. Figure 1 shows that the light is incident onto the surface and scattered in all directions above the reflecting surface S. In order to calculate conveniently,

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we assume the reflecting surface S lies in the xy plane of a Cartesian coordinate system. In this model, z axis is vertical to the surface, S, which is described in Figure 1. The light which is incident onto the surface is defined as the incident irradiance E_d (z, λ). The subscript d represents incident and λ is the wavelength. The field of view (FOV) of the sensor and the angle of reflection are the key factors to determine if the photons scattered by the optically shallow water can be recorded by the detector (Figure 2). It is notable that attention should paid to those scattered photons which have the ability to get the sensor. We noted the unique reflected path as CO which is used to represent how the scattered photos get the sensor O. We suppose that the layer can be segmented into enormous infinitesimals. Figure 2 shows that a beam of light Φ_{di} illuminates the jth volume Δv_j of thickness Δz_i. In this situation, a fraction of the collimated incident beam is scattered by S and get into a solid angle $\Delta\Omega_j$. The spectral volume scattering function (VSF) is described as [17, 18]:

$$\beta(\psi,\lambda)= \lim_{\Delta z_i \quad 0} \lim_{\Delta\Omega_j \quad 0} \left[\frac{\Phi_{si}}{\Phi_{di} \Delta z_i \Delta\Omega_j} \right] \tag{1}$$

Where Φ_{di} is the incident flux; Φ_{si} is the scattered fraction of incident light; ψ is the scattering angle between the forward direction of the light and the line between the scattering point C and the detector O. The part of the optically water column related to the upwelling radiant flux, Φ_u^{water}, is given by [19, 20]:

$$\Phi_u^{water} = \sum_j \sum_i \beta(\psi,\ \lambda) \cdot \lim_{\Delta z_i \to 0} \lim_{\Delta\Omega_j \to 0} \left[\Phi_{di} \cdot \Delta\Omega_j \cdot \Delta z_i \right] \tag{2}$$

The contribution of downwelling radiant flux, Φ_{di}, is defined as:

$$\Phi_{di} = \vec{E}_d(z,\lambda) \bullet \Delta\vec{s}_j \tag{3}$$

Where $\vec{E}_d(z,\ \lambda)$ is the downwelling irradiance at depth z; Φ_u^{water} is the part of upwelling radiant flux and is described as:

$$\Phi_u^{water} = \vec{E}_u^{water}(z,\lambda) \bullet \vec{s} \tag{4}$$

Where $\vec{E}_u^{water}(z, \lambda)$ is the fraction of the optically water column to the upwelling irradiance.

The scattering part of the upwelling irradiance is:

$$dE_u^{water}(z,\lambda) = E_d(z,\lambda) \cdot \beta(\Psi,\lambda) d\Omega dz \tag{5}$$

Kirk [21] defined $k_u(\lambda)$ as vertical diffuse attenuation coefficient for upward flux. Then Philpot introduced the parameter in [22]. $dE_u^{water}(z \to z^-_{surf}, \lambda)$ is the part of the upwelling irradiance from the considered layer to the subsurface:

$$dE_u^{water}(z \to z^-_{surf}, \lambda) = E_d(z,\lambda) \cdot \beta(\psi,\lambda) \cdot exp\left(-k_u(\lambda)\left(z - z^-_{surf}\right)\right) d\Omega dz \tag{6}$$

$E_d\,(z, \lambda)$ can be calculated as [23]:

$$E_d(z,\lambda) = E_d\left(z \to z^-_{surf}, \lambda\right) exp\left(-k_d(\lambda)\left(z - z^-_{surf}\right)\right) \tag{7}$$

Where k_d is the vertical diffuse attenuation coefficient for downwelling irradiance. $dE_u^{water}(z \to z^-_{surf}, \lambda)$ can be obtained by:

$$\begin{aligned} dE_u^{water}\left(z \to z^-_{surf}, \lambda\right) &= E_d\left(z \to z^-_{surf}, \lambda\right) \cdot \beta(\psi,\lambda) \\ &\cdot exp\left[-\left(k_u(\lambda) + k_d(\lambda)\right) \cdot \left(z - z_{surf}\right)\right] d\Omega dz \end{aligned} \tag{8}$$

Equation (8) can be further simplified as:

$$\begin{aligned} dE_u^{water}\left(z \to z^-_{surf}, \lambda\right) &= E_d\left(z \to z^-_{surf}, \lambda\right) \\ &\cdot exp\left(-2k(\lambda)\left(z - z_{surf}\right)\right) \cdot \beta(\psi,\lambda) d\Omega dz \end{aligned} \tag{9}$$

The total VSF $\beta(\psi, \lambda)$ can be described as [24]:

$$\beta(\psi,\lambda) = \beta_w(\psi,\lambda) + \beta_p(\psi,\lambda) \tag{10}$$

Where w and p represent pure sea water and particles, respectively. The VSF can be estimated as [25]:

$$\beta_w(\psi,\lambda) = \beta_w(90°,\lambda_0)\cdot\left(\frac{\lambda_0}{\lambda}\right)^{4.32}\cdot\left(1+0.835\cos^2\psi\right) \tag{11}$$

The particle VSF is estimated as [26]. Thus,

$$\beta_p(\psi,\lambda) = b_p(\lambda)\cdot\tilde{\beta}_p(\psi,\lambda) \tag{12}$$

Where b_p is the particle scattering coefficient and β_p is the particle phase function [27–29]. Here, the Henyey-Greenstein phase function [30] is selected:

$$\tilde{\beta}_{HG}(\psi) = \frac{1}{4\pi}\cdot\frac{1-g^2}{\left(1+g^2-2g cos\psi\right)^{3/2}} \tag{13}$$

Here g is used to adjust the relative amounts of forward and backward scattering in β_{HG}:

$$2\pi\int_{-1}^{1}\tilde{\beta}_{HG}(\psi)\cos\psi\, d\cos\psi = g \tag{14}$$

In which case $d\Omega=sin\psi d\omega d\psi$, the contribution from the water column, can be further deduced. By substituting equations (11)–(13) into (9), the flux by the water can be estimated as (see Figure 2):

$$\begin{aligned} dE_u^{water}\left(z\to z^-{}_{surf},\lambda\right) &= E_d\left(z\to z^-{}_{surf},\lambda\right)\cdot exp\left(-2k(\lambda)\left(z-z_{surf}\right)\right) \\ &\cdot\left(\beta_w(90°,\lambda_0)\cdot\left(\frac{\lambda_0}{\lambda}\right)^{4.32}\cdot\left(1+cos^2\psi\right)+\frac{b_p}{4\pi}\cdot\frac{1-g^2}{\left(1+g^2-2gcos\psi\right)^{3/2}}\right) \\ &\cdot sin\psi\, d\psi\, d\omega dz \end{aligned} \tag{15}$$

The irradiance of the water can be calculated:

$$\begin{aligned} E_u^{water}\left(z\to z^-{}_{surf},\lambda\right) &= \int_{z_{surf}}^{H+z_{surf}}\int_{\psi_1}^{\psi_2}\int_{0}^{2\pi} E_d\left(z\to z^-{}_{surf},\lambda\right)\cdot exp\left(-2k(\lambda)\left(z-z_{surf}\right)\right) \\ &\cdot\left(\beta_w(90°,\lambda_0)\cdot\left(\frac{\lambda_0}{\lambda}\right)^{4.32}\cdot\left(1+cos^2\psi\right)+\frac{b_p}{4\pi}\cdot\frac{1-g^2}{\left(1+g^2-2gcos\psi\right)^{3/2}}\right) \\ &\cdot sin\psi\, d\psi\, d\omega dz \end{aligned} \tag{16}$$

Where ψ_1, and ψ_2 can be estimated as:

$$\psi_1 = -\left(\alpha_0 + \theta_0 + \frac{FOV}{2}\right) + \pi \tag{17}$$

$$\psi_2 = -\left(\alpha_0 + \theta_0 - \frac{FOV}{2}\right) + \pi \tag{18}$$

Here, FOV is the field of view of the sensor, α_0 is the solar attitude and θ_0 is the view angle measured from the z axis. Integration of equation (16), $E_u^{water}(z \to z^-_{surf}, \lambda)$ can be expressed as:

$$\begin{aligned} E_u^{water}\left(z \to z^-_{surf}, \lambda\right) &= E_d\left(z \to z^-_{surf}, \lambda\right) \cdot \left(\frac{\exp\left(-2k(\lambda)\left(z - z_{surf}\right)\right) - 1}{-2k}\right) \\ &\cdot \left[-2\pi\beta_w\left(90°, \lambda_0\right) \cdot \left(\frac{\lambda_0}{\lambda}\right)^{4.32} \cdot \left(\cos\Psi + \frac{0.835}{3}\cos^3\Psi\right)\right. \\ &\left. - \frac{b_p}{2g} \cdot \frac{1 - g^2}{\left(1 + g^2 - 2g\cos\Psi\right)^{1/2}}\right]_{\psi_1}^{\psi_2} \end{aligned} \tag{19}$$

The subsurface irradiance reflectance can be estimated [31]. $R^{water}(0^-, \lambda)$ can be further expressed as:

$$\begin{aligned} R^{water}\left(0^-, \lambda\right) &= \frac{E_u^{water}\left(z \to z^-_{surf}, \lambda\right)}{E_d\left(z \to z^-_{surf}, \lambda\right)} = \left(\frac{\exp\left(-2k(\lambda)\left(z - z_{surf}\right)\right) - 1}{-2k}\right) \\ &\cdot \left[-2\pi\beta_w\left(90°, \lambda_0\right) \cdot \left(\frac{\lambda_0}{\lambda}\right)^{4.32} \cdot \left(\cos\Psi + \frac{0.835}{3}\cos^3\Psi\right)\right. \\ &\left. - \frac{b_p}{2g} \cdot \frac{1 - g^2}{\left(1 + g^2 - 2g\cos\Psi\right)^{1/2}}\right]_{\psi_1}^{\psi_2} \end{aligned} \tag{20}$$

The subsurface remote-sensing reflectance just beneath the sea surface [32, 33], $R_{rs}(0^-,\lambda)$, can be calculated as:

$$R_{rs}\left(0^{-},\lambda\right)=\frac{R\left(0^{-},\lambda\right)}{Q} \tag{21}$$

Q is the radio of the subsurface upward irradiance to radiance conversion factor [34]. Remote-sensing reflectance of the water column just beneath the sea surface $R_{rs}^{water}(0^{-},\lambda)$ can be estimated as:

$$\begin{aligned} R_{rs}^{water}\left(0^{-},\lambda\right) &= Q\cdot\frac{E_u^{water}\left(z\rightarrow z^{-}{}_{surf},\lambda\right)}{E_d\left(z\rightarrow z^{-}{}_{surf},\lambda\right)} = Q\cdot\left(\frac{\exp\left(-2k\left(\lambda\right)\left(z-z_{surf}\right)\right)-1}{-2k}\right) \\ &\cdot\left[-2\pi\beta_w\left(90°,\lambda_0\right)\cdot\left(\frac{\lambda_0}{\lambda}\right)^{4.32}\cdot\left(\cos\Psi+\frac{0.835}{3}\cos^3\Psi\right)\right. \\ &\left.-\frac{b_p}{2g}\cdot\frac{1-g^2}{\left(1+g^2-2g\cos\Psi\right)^{1/2}}\right]_{\psi_1}^{\psi_2} \end{aligned} \tag{22}$$

Finally, the bottom reflectance can be obtained by $R_{rs}{}^{b}$:

$$R_{rs}^{b}=R_{rs}\left(0^{-},\lambda\right)-R_{rs}^{water}\left(0^{-},\lambda\right) \tag{23}$$

3. Materials and methods

In situ survey was carried out in the Sanya Bay (109°25′–109°29′ E, 18°12′–18°13′ N) in the South China Sea on 15–20, April 2008(see **Figure 3**). *Thalassia* seagrass dominates in this area. Sanya Bay [35], which is a typical tropical bay, includes a broad range of habitats. Spectral irradiance was measured by using a spectrometer (S2000, Ocean Optics, Inc.) [36]. The instrument has a spectral resolution with 0.3 nm and bandwidths are from 200 to 1100 nm. Besides, a self-designed remote cosine receptor was used to measure signals proportional to the sky radiance, sea surface radiance and the radiance reflected from a horizontal reference panel by connecting to the S2000 with an optical fiber (P400-2-UV/VIS) with a FOV of 10°. The viewing angle was 40°.

Following the method in Mobley [37], the relative azimuth was set as 135°. The spectral downwelling radiance was measured from a reflectance panel $L_g(\lambda)$ (Spectralon). The reflectance of Spectralon is known, and the relationship between the measured radiance and the incident irradiance $E_d(\lambda)$ is given by:

$$E_d(\lambda) = q(\lambda) \cdot \frac{1}{\rho} \cdot L_g(\lambda) \tag{24}$$

$q(\lambda)$ is an angular and wavelength-dependent factor, and ρ_g is the irradiance reflectance of Spectralon. Clear sky conditions are necessary to in situ survey. 100 shoots of seagrass were selected to count leaf number *jj*, and also to calculate the percentage of shoots with *jj* leaves X_{jj}. Ten shoots with the same leaf number were selected. The leaves were centered on a box (25 cm×40 cm), and then took a photo to record the situation. Based on the pixels of seagrass in the photos, M_{jj}, the average leaf area of seagrass with the different numbers of leaves can be recorded. The leaf area index M can be estimated as:

$$M = P \times \sum \left(i \times M_{jj} \times X_{jj} \right) \tag{25}$$

Here P represents the seagrass density of each processing (shoots/m^2).

4. Results

The algorithm was employed to obtain the bottom reflectance. Based on the results the seagrass information which was retrieved from the modeled $R_{rs}{}^{b}$ is reasonable to. In Figure 4, between 550 nm and 750 nm the predicted value $R_{rs}{}^{b}$ agreed very well with the *in situ* measured bottom reflectance $R_{rs}{}^{b}$. Between 600 and 800 nm, $R_{rs}{}^{b}$ was found to be lower than subsurface remote-sensing reflectance $R_{rs}(0^{-})$. This error could be related to the absorption and scattering properties of the optically shallow water which mainly affect the spectral reflectance at this band.

It is noted that the subsurface reflectance cannot be used directly to classify the bottom type or substitute the bottom reflectance. We provided a comparison between the subsurface remote sensing reflectance and the remote sensing reflectance of the bottom. The results also illustrate the conclusion in Figure 5(a). It was found that there does indeed exist a considerable difference between the subsurface remote sensing reflectance $R_{rs}(0^{-})$ and the remote sensing reflectance of the bottom $R_{rs}{}^{b}$. Compared to the subsurface reflectance, the retrieved bottom reflectance is more related to in situ measured ones in Figure 5(b). It was found that there is a significant relationship between *in situ* measured $R_{rs}{}^{b}$ values and modeled ones. Therefore, it is safe to conclude that $R_{rs}(0^{-})$ cannot be used directly to represent the hyperspectral recognition of seagrass in optically shallow waters is unfitted.

The seagrass reflectance with different LAI (Leaf Area Index) was surveyed to evaluate the relationship between the spectral characteristics of seagrass and also validate the sensitivity bands to LAI. The retrieved bottom reflectance can represent the typical optical properties of seagrass very well than the subsurface remote-sensing reflectance (see Figures 6(a) and (b)). Based on Figure 6(b), it is found that the typical optical characteristics of the seagrass are obvious. In addition, a spectral peak shift from the red edge to the red with leaf areas is increasing. It was found that 555, 650, 675 and 700 nm are relatively good bands to extract LAI information in Figure 6(b). In these regions, an excellent separation among the different LAI index can be done. These bands correspond to the absorption troughs and reflectance peaks, which were also related to the photosynthetic and accessory pigments. Large variations in chlorophyll contents in seagrass leaves could determine a relatively small part of leaf absorptance. Figure 6(b) shows the properties between 680 and 720 nm in the leaves' spectrum at the different sites. The evident phenomenon is related to the package effect. It was found that the pigment self-shading among thylakoid layers could affect the light absorption and the harvesting efficiency, and thereby the chlorophyll concentration is not linear with the light harvesting efficiency [38]. Cummings and Zimmerman [27], and Enriquez [28] also observed the strong package effect in seagrass, and they concluded that it attributed to the restriction of chloroplasts to the leaf epidermis. Figures 6(c) and (d) show that there is not an obvious relationship between subsurface remote sensing reflectance at 715 nm and LAI. On the contrary, there is a relatively significant relationship between the retrieved bottom reflectance at 715 nm and LAI. This phenomenon also proves that this algorithm is effective to map seagrass distribution and bottom classification.

In Figure 6(b), it was found that the reflectance of Thalassia increased from 518 to 532 nm. This phenomenon was related to the changes in xanthophyll-cycle pigmentation. In addition, the leaves of Thalassia were found to display an olive-drab color in the South China Sea, and that properties was related the peak of the retrieved bottom reflectance curve near 550 nm (see Figure 6(b)). A spectral region of maximum reflectance was found between 800 and 840 nm. It is the typical spectral reflectance of aquatic plants. Based on the spectrum analysis, the modeled bottom reflectance retrieved by the improved algorithm can be used to represent the typical optical properties of seagrass.

5. Conclusions

An improved optically shallow water algorithm was provided to model the radiation transfer. In the model, the water body was considered as a multilayer, heterogenous, nonhomogenous, natural media. The algorithm could adjust the input parameter to the equation with the different optical properties in water column for retrieving bottom reflectance. The equations which were used to retrieve bottom reflectance or to quantify the benthos can keep the same form. The method could model a wide range of the optical characteristics for radiation fields in these layers. These properties are useful to simulate any contribution of each region and learn the mechanisms of the formation of the radiation characteristics inside and outside the layers. The algorithm can appropriately minimize the effects of the optically shallow water on the remotely sensed signal to obtain an estimate of the reflectance of seagrass.

Based on the results and analysis, the method was proved to be valid for improving the accuracy of bottom mapping. The water column correction algorithm is necessary to retrieve the empirical relationships between satellite data and the interesting features in the optically shallow water. Through the implementation of the algorithm and results analysis between 500–630 nm and 680–710 nm were found to be more effective to discriminate and map seagrass meadows of the Sanya Bay. Therefore, an appropriate spectral band for seagrass mapping should include the narrow bands centered 555, 650, 675 and 700 nm (maximum bandwidth 5–10 nm). A strong correlation coefficient of 0.99 existed between the bottom reflectance at 715 nm retrieved by the water column correction algorithm and LAI. The input parameters for the algorithm in the study are the remote sensing reflectance from the subsurface. In order to apply the algorithm to the satellite images, the atmosphere correction should be taken into account. The atmosphere influence has a great contribution to affect the blue band. In order to improve the accuracy of the surface reflectance, it could be acquired through further development of the theory and models for the atmospheric correction. Therefore, the reflectance at 715 nm could be used to estimate LAI of seagrass.

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