Applying narrowband remote-sensing reflectance models to wideband data

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Remote sensing of coastal and inland waters requires sensors to have a high spatial resolution to cover the spatial variation of biogeochemical properties in fine scales. High spatial-resolution sensors, however, are usually equipped with spectral bands that are wide in bandwidth (50 nm or wider). In this study, based on numerical simulations of hyperspectral remote-sensing reflectance of optically-deep waters, and using Landsat band specifics as an example, the impact of a wide spectral channel on remote sensing is analyzed. It is found that simple adoption of a narrowband model may result in >20% underestimation in calculated remote-sensing reflectance, and inversely may result in >20% overestimation in inverted absorption coefficients even under perfect conditions, although smaller (∼5%) uncertainties are found for higher absorbing waters. These results provide a cautious note, but also a justification for turbid coastal waters, on applying narrowband models to wideband data. © 2009 Optical Society of America

1. Introduction

Ocean color remote sensing utilizes radiometric data to derive, empirically or analytically, desired information of subsurface constituents [1,2]. Operationally, two types of satellite sensors are commonly employed for the measurement of ocean color (spectral upwelling radiance from below the surface that emits to space). These sensors are contrasted by their specifics in data collection: one sensor (such as the Moderate Resolution Imaging Spectroradiometer (MODIS) [3]) has medium (or low) spatial resolution (a footprint of hundreds of meters or larger) with a narrow bandwidth (20 nm or narrower), while the other (such as the Landsat [4], IKONOS [5], Quick-Bird [6], or Advanced Land Observing Satellite (ALOS) [7]) has a high spatial resolution (a footprint of 30 m or finer) with a wide bandwidth (50 nm or wider). Because of such contrast in their sensor characteristics, the data collected by these sensors have different applicability. For remote sensing of oceanic waters, where in general, horizontal gradients of the biogeochemical properties are mild, data with medium to low spatial resolution are sufficient [8]. For remote sensing of coastal and inland waters, however, due to reasons from small target areas to land/river runoff effects, it requires sensors with high spatial resolution to observe the intense geophysical variations within a short distance. Such a difference in the requirement of spatial resolution has an impact on sensor designs. Because the pixel size of medium-resolution data (MRD) is ∼10–30 times larger than that of high-resolution data (HRD), a sensor for MRD is able to reduce the bandwidth of the spectral channels to about 10–20 nm and still maintain a high signal-to-noise ratio (SNR), which is critical for reliably deriving subsurface properties. For the case of HRD, there are two options to obtain higher SNR: one option is to increase the integration time, but this is impractical for polar orbiting satellites, and prolonged integration time will decrease the sharpness of an image; the other is to increase the bandwidth of the spectral channels, as demonstrated by the operational Landsat satellite, where the bandwidths are ∼50–70 nm.

For coastal and inland remote sensing, HRD is required for meaningful and useful measurements

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of water quality (such as concentration of chlorophyll, load of suspended sediments, and water clarity). Experimental sensors with both high spatial and spectral resolutions (such as Hyperion on EO1 [9]) have shown great promise for coastal remote sensing [10,11], but their SNRs are far from optimal for remote sensing of oceanic waters. Numerous studies have been carried out to obtain coastal biogeochemical information from Landsat measurements (e.g., Dekker et al. [12], Hellweg et al. [13], and Vincent et al. [14]). For the derivation of water-quality parameters from HRD, generally there are two schools of approaches: one is via empirical regressions (e.g., Vincent et al. [14], Zhang et al. [15], and Stumpf et al. [16]), and the other is via analytical or semianalytical models (e.g., Dekker et al. [12], Doxaran et al. [17], and Heng et al. [18]). Empirical approaches basically compile concurrent (or near concurrent) in situ and satellite data and link the two data sources statistically to achieve optimal regression coefficients for a desired product (e.g., chlorophyll concentration or Secchi depth). The empirical coefficients from such exercises are normally best applicable to the research areas and/or to the seasons where the data are taken. They are, because of wide variations of bio-optical properties [19], in general, less applicable to other regions or at other seasons. To overcome such limitations and to better characterize product uncertainties, it is desired and useful to take approaches that are based on analytical or semianalytical models.

For data from narrowband sensors (e.g., sea-viewing wide field-of-view sensor or MODIS), semianalytical models [20,21] based on the radiative transfer equation have been developed to describe the remote-sensing reflectance \( R_{rs} \), which is defined as the ratio of water-leaving radiance \( (L_w, w/(m^2 \text{ nm} \text{ sr})) \) to downwelling irradiance \( (E_d, w/(m^2 \text{ nm})) \) just above the surface, i.e.,

\[
R_{rs}(\lambda_i^W) = \frac{L_w(\lambda_i^W)}{E_d(\lambda_i^W)}.
\]  

(1)

Here \( \lambda_i^W \) is the center wavelength of band \( i \).

For optically-deep waters, the semianalytical models for \( R_{rs} \) can be summarized into a generalized mathematical form [20]:

\[
R_{rs}(\lambda_i^W) = G(\lambda_i^W) \frac{b_b(\lambda_i^W)}{\bar{a}(\lambda_i^W) + b_b(\lambda_i^W)}.
\]  

(2)

Here \( G \) is a model parameter that varies with water’s inherent optical properties (IOPs) [22], \( \bar{a} (m^{-1}) \) is the total absorption coefficient, and \( b_b (m^{-1}) \) is the total backscattering coefficient. With models like this, various algorithms have been developed to retrieve subsurface physical and biogeochemical properties [23–25].

There are no semianalytical models developed specifically for \( R_{rs} \) from wide band sensors (WBS). Usually the models developed for narrowband sensors are applied directly (e.g., Doxaran et al. [17]), with IOPs considered as their corresponding averages at each band, i.e.,

\[
R_{rs}(\lambda_i^W) = \frac{G(\lambda_i^W)}{\bar{a}(\lambda_i^W) + b_b(\lambda_i^W)}.
\]  

(3)

Here \( b_b \) and \( \bar{a} \) are band-averaged values at each WBS channel \( \lambda_i^W \). As model parameter \( G \) is commonly considered as a function of \( b_b/(\bar{a} + b_b) \) \[20\], \( G(\lambda_i^W) \) can be evaluated with the band-averaged \( b_b \) and \( \bar{a} \) values.

For remote sensing by a WBS, however, the measured remote-sensing reflectance at band \( i \) is

\[
R_{rs}(\lambda_i^W) = \frac{\int_{\lambda_i^W}^{\lambda_i^W} L_w(\lambda) d\lambda}{\int_{\lambda_3}^{\lambda_8} E_d(\lambda) d\lambda},
\]  

(4)

with \( \lambda_i^W \) and \( \lambda_i^W \) the lower and upper wavelength boundaries for band \( i \), respectively. Here the sensor’s response function at each band is considered as a perfect boxcar function and then omitted in the expression and in this study. Based on Eqs. (1) and (2), the exact model formulation for remote-sensing reflectance of optically-deep water measured by a WBS is

\[
R_{rs}(\lambda_i^W) = \int_{\lambda_i^W}^{\lambda_i^W} G(\lambda) \frac{b_b(\lambda)}{\kappa(\lambda)} E_d(\lambda) d\lambda / \int_{\lambda_i^W}^{\lambda_i^W} E_d(\lambda) d\lambda,
\]  

(5)

with \( \kappa = \bar{a} + b_b \).

Because \( E_d(\lambda) \) is not spectrally constant, mathematically and strictly speaking,

\[
R_{rs}(\lambda_i^W) \neq \int_{\lambda_i^W}^{\lambda_i^W} G(\lambda) \frac{b_b(\lambda)}{\kappa(\lambda)} d\lambda.
\]  

(6)

Furthermore, \( G, b_b, \) and \( \kappa \) (in particular the absorption spectrum) spectra are spectrally dependent (see Mobley [26]) and, from mathematical principles,

\[
R_{rs}(\lambda_i^W) \neq \int_{\lambda_i^W}^{\lambda_i^W} G(\lambda) d\lambda \frac{\int_{\lambda_i^W}^{\lambda_i^W} b_b(\lambda) d\lambda}{\int_{\lambda_i^W}^{\lambda_i^W} \kappa(\lambda) d\lambda}.
\]  

(7)

Therefore,

\[
R_{rs}(\lambda_i^W) \neq \frac{\bar{G}(\lambda_i^W)}{\bar{a}(\lambda_i^W) + b_b(\lambda_i^W)}.
\]  

(8)

Consequently, if we want to utilize Eq. (3) (for the sake of simplicity) to represent \( R_{rs} \) data measured by a WBS, it is necessary and important to know how big the difference is between \( R_{rs} \) from Eq. (5) (the exact form) and \( R_{rs} \) from Eq. (3) (the approximation), how this difference varies with water properties, and the likely impacts when this simple form is
utilized for remote-sensing applications. To find out and to understand the potential uncertainties and impacts associated with the simple model, using Landsat band specifics as an example, $R_{rs}(\lambda^W)$ values between the simple form and the spectrally-resolved form are evaluated for various IOPs in this study, as are the impacts of Eq. (3) on IOP inversions when it is applied to WBS data.

2. Numerical Analysis

To evaluate the likely errors associated with the simple approximation [Eq. (3)], a series of numerical simulations with various hyperspectral IOP values were carried out. For this evaluation, a hyperspectral (400–900 nm, with an interval of 5 nm), nadir-viewing $R_{rs}(\lambda)$ is simulated first with the following equations [23]:

$$R_{rs} = \frac{0.52r_{rs}}{1 - 1.7r_{rs}}, \quad (9)$$

$$r_{rs} = \left(0.089 + 0.125\frac{b_w}{\kappa}\right)\frac{b_w}{\kappa}. \quad (10)$$

Here $r_{rs}$ is the nadir-viewing remote-sensing reflectance just below the sea surface, and wavelength dependence is omitted for brevity. $b_w$ and $b_{bp}$ ($b_{bp} = b_{bw} + b_{bp}$) are the backscattering coefficients of pure water and particles, respectively; $\kappa$ includes the contributions of absorption coefficients of pure water ($a_w$), phytoplankton pigments ($a_{ph}$), and detritus plus colored dissolved organic matter ($a_{dg}$).

For the calculation of $R_{rs}$ spectra, hyperspectral absorption and backscattering coefficients are generated with the following inputs: (1) Values of $a_w(\lambda)$ are from Pope and Fry [27] (400–695 nm) and Hale and Querry [28] (700–900 nm). $a_w$ values of Hale and Querry are raised by 4% to match the $a_w$ value of Pope and Fry at 700 nm. Figure 1 shows the $a_w$ spectrum used in this study. (2) Values of $b_w(\lambda)$ are from Morel [29]; (3) $a_{ph}(\lambda)$ is modeled as in Lee et al. [30] with $a_{ph}(440)$ values ranging 0.005–5.0 m$^{-1}$. For $\lambda > 720$ nm, $a_{ph}(\lambda)$ is considered as equal to $a_{ph}(720)$. (4) $a_{dg}(\lambda)$ is modeled as an exponential function of wavelength [31] scaled by $a_{dg}(440)$, with a spectral slope of 0.019 nm$^{-1}$ and $a_{dg}(440)$ values ranging 0.005–5.0 m$^{-1}$. (5) $b_{bp}(\lambda)$ is modeled as a power-law function of wavelength [19] scaled by $b_{bp}(440)$, with an exponent of 0.5 and $b_{bp}(440)$ values ranging 0.002–2.0 m$^{-1}$. A total of 12 sets of IOPs were created covering an $a(440)$ range of $\sim 0.016$–10.0 m$^{-1}$ and a $b_p(440)$ range of $\sim 0.004$–2.0 m$^{-1}$, where $a(440)$ and $b_p(440)$ values are not covarying and cover the general range of oceanic and continental waters [32]. As the focus here is to observe the potential uncertainties introduced by a simple model like Eq. (3), it is not necessary to carryout simulations with all possible combinations of IOPs observed in natural waters, although that might be required for the development of an optimal scheme to correct the wideband effects.

Landsat has four bands in the visible to near infrared that could be used for water remote sensing. The bands are Band 1 (450–520 nm), Band 2 (520–600 nm), Band 3 (630–690 nm), and Band 4 (770–900 nm). For these Landsat bands, the variation of $E_d(\lambda)$ within a band is less than $\sim 20\%$ (see Fig. 1). Further, because $R_{rs}(\lambda)$ is derived by normalizing the total $L_w$ (which is proportional to $E_d$) to the total $E_d$ within a band [see Eq. (4)], the impact on $R_{rs}(\lambda^W)$ from $E_d$ spectral variation within a band is negligible ($\sim 1\%$); therefore Eq. (5) can be well approximated as

$$R_{rs}(\lambda^W) \approx \int_{\lambda'}^{\lambda} R_{rs}(\lambda) d\lambda. \quad (11)$$

With the simulated hyperspectral absorption and backscattering coefficients, it is now straightforward to calculate and compare $R_{rs}(\lambda^W)$ values from Eq. (3) and from Eqs. (9)–(11), respectively. To be consistent, $R_{rs}(\lambda^W)$ from Eq. (3) also utilized Eqs. (9) and (10), but simply with band-averaged total backscattering and total absorption coefficients as inputs. Note that here sensor’s response function of each Landsat band is omitted as it is nearly flat spectrally (within $\pm 10\%$) for the primary portion of the bands [33].

If the sensor’s response function significantly deviates from a perfect boxcar function, it should be included in the integrations of Eqs. (4) and (11) as in Bukata et al. [34]. Also, if a band covers the 400–450 nm range, or any other ranges that contain significant spectral variations of $E_d$, larger impacts on $R_{rs}(\lambda^W)$ from $E_d(\lambda)$ variation could be expected and a more strict formulation like Eq. (5) should be applied.

3. Results and Discussion

Figure 2 presents examples of simulated hyperspectral $R_{rs}$ (solid line) and $R_{rs}(\lambda^W)$ calculated by Eq. (3) (open square) and by Eq. (11) (solid circle), respectively. These circles and squares represent $R_{rs}$ at
the center wavelengths of the Landsat bands. As demonstrated in Dekker et al. [12,35], expanding the bandwidth of the spectral channels will diminish the sharpness of the spectral features on which remote sensing of geophysical information relies. Furthermore, it is not surprising to see that values of $R_{rs}(\lambda_{Wi})$ calculated from Eqs. (3) and (11) are different for various IOP combinations, and the differences are not uniform. To quantify the error of the simple approximation [Eq. (3)], Fig. 3 shows the percentage difference, $100 \times (\text{Eq. 3} - \text{Eq. 11})/\text{Eq.11}$, for $R_{rs}(\lambda_{Wi})$ at the four Landsat bands, along with their relationships with the total absorption coefficient at 440 nm. It is found that all $R_{rs}(\lambda_{Wi})$ from Eq. (3) are smaller than that from Eq. (11), and the difference can be as large as $\sim 24\%$. The differences at Bands 1–3 are much smaller ($\sim 5\%$), however, for relatively turbid waters ($\alpha(440) \sim 0.3 \text{ m}^{-1}$), which provide a fundamental justification of applying forms like Eq. (3) to WBS data over coastal turbid waters.

Because different IOPs (especially the spectral selective characteristics of the absorption coefficient) have different impacts on $R_{rs}(\lambda_{Wi})$, errors associated with $R_{rs}(\lambda_{Wi})$ at the four Landsat bands are not uniform. Both Band 1 (centered at 485 nm) and Band 2 (centered at 560 nm) experienced highest $R_{rs}(\lambda_{Wi})$ difference between Eqs. (3) and (11) when there are fewer dissolved and/or suspended constituents in water. This is because there are sharp (about 4–5 times) increases of absorption coefficients of pure water that Band 1 and Band 2 cover (see Fig. 1). These values dominate the total absorption coefficient when waters are clearer. Mathematically, for a series of values of $x_i$ that contains wide range of lower to higher values, the inverse ($1/x$) of the series' average ($\bar{x}$) is influenced more by the higher $x_i$ values, while the
average of the individual $x_i$’s inverse ($\frac{1}{x_i}$) is influenced more by the lower $x_i$ values. These facts explain why $R_{rs}(\lambda_i^w)$, which is in general inversely related to total absorption coefficient, by Eq. (3) is smaller than that by Eq. (11), and why there could be big difference between $R_{rs}$ from Eq. (3) and $R_{rs}$ from Eq. (11). Further, this fact implies that, if Eq. (3) is used for semi analytical retrieval of water’s IOPs, the inverted total absorption coefficient of a wideband does not represent the band-averaged total absorption coefficient at that band (see below).

When there are more dissolved and suspended constituents (such as gelbstoff and phytoplankton) in water, because they contribute most to the absorption coefficients at the shorter wavelengths and the contributions are spectrally broad, the spectral feature of pure water absorption diminishes gradually. Consequently, the $R_{rs}(\lambda_i^w)$ error at Band 1 and Band 2 reduces to $\sim5\%$.

At Band 3 (centered at 660 nm) and Band 4 (centered at 835 nm), on the other hand, because the contribution from pure water dominates the total absorption spectrum, the differences do not vary much across the various IOPs. The difference of $R_{rs}(\lambda_i^w)$ at Band 3, however, is smaller ($\sim5\%$) than that at Band 4 ($\sim15\%$), because at Band 3 $a_w$ only varies in a range of $\sim0.3$–0.5 m$^{-1}$, while at Band 4 it varies from $\sim2$ to 6 m$^{-1}$.

To test the impact of wideband data and a simple wideband model [Eq. (3)] on IOP retrievals, Eq. (11)-simulated $R_{rs}(\lambda_i^w)$ were used as inputs to derive particle backscattering and total absorption coefficients following the quasi-analytical algorithm (QAA) approach [23,36]. In the process, Landsat Band 2 (with center wavelength of 560 nm) was considered as the reference wavelength [23], and the actual band-averaged total absorption coefficients were used, i.e., assuming a perfect estimation of absorption coefficient at the reference wavelength. With known $R_{rs}(B2)$ and $a(B2)$, $b_{bp}(B2)$ at this band can be derived algebraically as in Lee et al. [23]. Propagate this $b_{bp}$ to Band 1 (with center wavelength of 485 nm) with the known exponent (0.5, again, assuming a perfect estimation), $a(B1)$ is then derived from known $R_{rs}(B1)$. Figure 4 compares the derived $a(B1)$ with the known band-averaged values (open circle) as well as $a(485)$—the absorption coefficients at the center wavelength (dark square). Clearly, when no corrections are made for the wideband effects, it could result in $20\%$ overestimation of $a(B1)$ even under ideal conditions. In reality, especially for complex coastal waters, larger uncertainties are associated with the estimation of the absorption coefficients at Band 2 and the exponent for the particle backscattering coefficient, and consequently larger uncertainties of remotely derived $a(B1)$ would be expected [37].

For waters with higher absorption coefficients ($a(B1) > \sim0.2$ m$^{-1}$), however, the QAA inverted $a(B1)$ (under ideal conditions) are quite consistent (within $\pm5\%$) with known $a(B1)$ values, at least for the limited data in this study. Such theoretical and numerical results provide a justification for applying narrowband semi-analytical models with wideband data over turbid waters (e.g., Heng et al. [18]), although fine adjustments might be necessary to reflect band specifics and data characteristics. But, as indicated earlier, wideband derived absorption coefficients cannot be compared with narrowband measurements, where a systematic overestimation is expected (see Fig. 4, data with square symbol).

Note that the effects of wide bandwidth on atmospheric correction is not discussed here, as it is out of the scope of this study and that various approaches to achieve satisfactory atmosphere correction can be found in Hu et al. [38] and Liang et al. [39]. Because empirical approaches of remote sensing directly link desired products with sensor measured data, the bandwidth effects are implicitly imbedded in the empirical coefficients and, therefore, no extra correction is necessary. The derived empirical coefficients, however, are usually site, season, and sensor specific, and therefore not easily transferable and/or applicable globally.

4. Conclusions

Remote-sensing systems with high spatial resolution (~30 m or finer) capability are required for monitoring coastal and inland waters. Such systems usually carry sensors with spectral channels that are wide (~50 nm or wider) in bandwidth to achieve desired SNRs. For optically-deep waters, such a wide bandwidth can cause more than 20% underestimation in modeled values if a narrowband remote-sensing reflectance model with band-averaged IOPs are simply applied. Inversely, applying a narrowband model to wideband reflectance data may result in

![Graph showing percentage difference for Band 1 vs. Band 3 absorption coefficients.](image-url)
20% overestimation of the inverted absorption coefficient, at least at Band 1 when water is relatively clear. The differences can be larger or smaller as they are dependent on IOPs, as well as on band location and bandwidth. For Landsat Bands 1–3, we found that for turbid waters \((a(440) > \sim 0.3 \text{ m}^{-1})\) the bandwidth-introduced uncertainties are relatively small (<5%), which justifies the applications \([12,18]\) of narrowband semianalytical models with such wideband data for coastal remote sensing.

Since remote-sensing reflectance is, in general, inversely dependent on the absorption coefficient, underestimation of this reflectance is also expected if a narrowband remote-sensing model developed for optically shallow waters (e.g., Maritorena et al. \([40]\), Lee et al. \([41]\)) is simply applied to WBS data collected over shallow regions, and its analytical inversion will be more problematic because of the wideband effect and the limited spectral channels \([42]\).

To achieve accurate vicarious calibrations \([43]\), or to better retrieve water’s physical and biogeoophysical properties, however, the bandwidth related uncertainties need to be accounted for, especially when waters are relatively clearer. Separately, because the band specifications of many others (such as IKONOS, ALOS, and QuickBird) are nearly identical to that of Landsat, the results and conclusions presented here are, in general, applicable to those sensors.

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