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Re-parameterization of a quasi-analytical algorithm for colored dissolved organic matter dominant inland waters

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ABSTRACT

Quasi-Analytical Algorithms (QAAs) are based on radiative transfer equations and have been used to derive inherent optical properties (IOPs) from the above surface remote sensing reflectance (R_{rs}) in aquatic systems in which phytoplankton is the dominant optically active constituents (OACs). However, Colored Dissolved Organic Matter (CDOM) and Non Algal Particles (NAP) can also be dominant OACs in water bodies and till now a QAA has not been parametrized for these aquatic systems. In this study, we compared the performance of three widely used QAAs in two CDOM dominated aquatic systems which were unsuccessful in retrieving the spectral shape of IOPS and produced minimum errors of 350% for the total absorption coefficient (a), 39% for colored dissolved matter absorption coefficient (a_{CDM}) and 7566.33% for phytoplankton absorption coefficient (a_{phy}). We re-parameterized a QAA for CDOM dominated (hereafter QAA_{CDOM}) waters which was able to not only achieve the spectral shape of the OACs absorption coefficients but also brought the error magnitude to a reasonable level. The average errors found for the 400–750 nm range were 30.71 and 14.51 for a, 14.89 and 8.95 for a_{CDM} and 25.90 and 29.76 for a_{phy} in Funil and Itumbiara Reservoirs, Brazil respectively. Although QAA_{CDOM} showed significant promise for retrieving IOPs in CDOM dominated waters, results indicated further tuning is needed in the estimation of $a(\lambda)$ and $a_{phy}(\lambda)$. Successful retrieval of the absorption coefficients by QAA_{CDOM} would be very useful in monitoring the spatio-temporal variability of IOPS in CDOM dominated waters.

1. Introduction

Chlorophyll-*a* (chl-*a*, refer to Table 1 for symbols and acronyms) concentration is essential for monitoring water quality in aquatic systems since it is an estimator of their trophic state. It is also an indicator of primary production and algal blooms, especially toxic cyanobacterial blooms in reservoirs, lakes, and estuaries (Reinart and Kutser, 2006). Chl-*a* is often considered as a proxy for algal biomass and has been used as an indicator of ecological health of waters. Traditional monitoring methods of chl-*a* are based on field sampling and laboratory analysis which are expensive and time consuming (Duan et al., 2010). Moreover, their spatial and temporal heterogeneity make point field sampling inadequate for monitoring large areas (Gons, 1999). Remote sensing techniques have been extensively used for monitoring chl-*a* in aquatic inland systems (Dall'Olmo and Gitelson, 2005; Gitelson et al., 2007, 2008, 2009; Le et al., 2009a, 2011; Mishra and Mishra, 2012). Advantages in remote monitoring are: (1) synoptic view of satellite images allow the acquisition of data from the entire aquatic system; (2) the capability of obtaining information from remote and sometimes inaccessible regions; and (3) the availability of historical series of data allowing the extraction of information from the past (Hadjimitsis and Clayton, 2009). Accordingly, Gons (1999) observed that the use of remote sensing techniques were time saving, cost-effective, and scientifically rewarding alternative.

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Table 1
List of symbols and acronyms on bio-optical modeling.

Symbol/acronym	Description	Unit
IOPs	Inherent optical properties	–
AOPs	Apparent optical properties	–
QAA	Quasi-analytical algorithm	–
CDOM	Colored dissolved organic matter	–
NAP	Non algal particles	–
CDM	Colored detritus matter (CDOM + NAP)	–
chl-*a*	Chlorophyll-*a*	–
PC	Phycocyanin	–
Q	Light distribution factor	sr
f	Geometrical light factor	
R_{rs}	Remote sensing reflectance above water surface	sr^{-1}
r_{rs}	Remote sensing reflectance below water surface	sr^{-1}
$L_u(0^-, \lambda)$	Spectral Upwelling radiance below water surface	$W\,m^{-2}\,sr^{-1}$
$L_{sky}(0^-, \lambda)$	Sky radiance	$W\,m^{-2}\,sr^{-1}$
$L_{ref}(0^-, \lambda)$	Spectralon reference panel radiance	$W\,m^{-2}\,sr^{-1}$
$L_w(0^-, \lambda)$	Water leaving radiance	$W\,m^{-2}\,sr^{-1}$
$E_d(0^-, \lambda)$	Spectral downwelling irradiance bellow water surface	$W\,m^{-2}\,sr^{-1}$
$E_s(0^+, \lambda)$	Spectral incident irradiance above water surface	$W\,m^{-2}\,sr^{-1}$
$a(\lambda)$	Spectral total absorption coefficient	m^{-1}
$a_p(\lambda)$	Spectral absorption coefficient of particulate matter	m^{-1}
$a_{phy}(\lambda)$	Spectral absorption coefficient of phytoplankton	m^{-1}
$a_{NAP}(\lambda)$	Spectral absorption coefficient of non-algal particles	m^{-1}
$a_{CDM}(\lambda)$	Spectral absorption coefficient of colored detritus matter	m^{-1}
$a_{CDOM}(\lambda)$	Spectral absorption coefficient of colored dissolved organic matter	m^{-1}
$a_w(\lambda)$	Spectral absorption coefficient of pure water	m^{-1}
$b_b(\lambda)$	Spectral total backscattering coefficient	m^{-1}
$b_{b,w}(\lambda)$	Spectral backscattering coefficient of pure water	m^{-1}
$b_{b,p}(\lambda)$	Spectral backscattering coefficient of particulate matter	m^{-1}
$b_{b,phy}(\lambda)$	Spectral backscattering coefficient of phytoplankton	m^{-1}
$b_{b,NAP}(\lambda)$	Spectral backscattering coefficient of non-algal particles	m^{-1}
[chl-*a*]	Chlorophyll-*a* concentration	μg/L
[NAP]	Non algal particles concentration	mg/L

Remote sensing of chl-*a* is based on relating different spectral characteristics of chl-*a* such as absorption, scattering, and fluorescence in mathematical or physical algorithms. These algorithms, also known as bio-optical models, have been applied on aquatic systems worldwide and can be classified into three categories: semi-empirical, semi-analytical, and quasi-analytical (Odermatt et al., 2012). Semi-empirical algorithms such as red-near infrared (NIR) band ratio (Dall'Olmo and Gitelson, 2005; Moses et al., 2009), fluorescence line height (Gons et al., 2008; Hu et al., 2005), three-band tuning algorithms (Dall'Olmo and Gitelson, 2005; Gitelson et al., 2007, 2008, 2009), four-band algorithms (Le et al., 2009b) and Normalized Difference Chlorophyll Index (NDCI) (Mishra and Mishra, 2012) have been used to monitor chl-*a* in inland waters. However, they are usually limited to the environmental conditions of the specific aquatic system and empirical calibrations are often required (Matthews et al., 2010). On the other hand, analytical algorithms are based on radiative transfer equations and since it is based on physical principles, they should be useful in different water bodies (Li et al., 2013). Therefore, the International Ocean Colour Coordinating Group (IOCCG) suggested deriving inherent optical properties (IOPs) rather than directly estimating chl-*a* concentration from the above-surface remote sensing reflectance (R_{rs}) for highly turbid inland waters (IOCCG, 2006; Li et al., 2011, 2013, 2015; Gons et al., 2002; Mishra et al., 2013, 2014). That way, the estimated absorption coefficient of phytoplankton (a_{phy}) can be used to quantify chl-*a* concentration (Gilerson et al., 2010; Li et al., 2013). These IOP decomposition algorithms first proposed by Lee et al. (2002) are termed as quasi-analytical algorithms (QAA).

QAAs have been proposed to estimate the IOPs from ocean waters (Lee et al., 2002, 2009) and several re-parameterized versions have been used for in inland waters (Li et al., 2013, 2015; Mishra et al., 2014). However, all the previously published versions of QAA in the literature are found to be calibrated and validated in aquatic systems in which a_{phy} was the dominant IOP. Therefore, the use of those QAAs for monitoring chl-*a* in aquatic systems in which phytoplankton is not the dominant component is still a challenge (Gons et al., 2008; Li et al., 2013), mainly due to the dominance of other optically active constituents (OACs) such as colored dissolved organic matter (CDOM) and non-algal particles (NAP). These two constituents have absorption features that usually overlap with chl-*a* mainly in the blue and green spectral channels. These characteristics do not allow the existing QAAs to accurately retrieve IOPs in waters dominated by CDOM and NAP, since most of the bands used in the QAAs are located in the blue and green wavelengths.

The main goal of the present study was to parameterize an existing QAA to retrieve the IOPs in CDOM dominated waters, since to the best of our knowledge, there has not been any semi-analytical model or QAA developed or parameterized specifically for CDOM dominated tropical inland waters. The objectives of this research were: (1) to evaluate the performance of the existing QAA using *in situ* and bio-optical dataset acquired from two CDOM dominated tropical reservoirs; and (2) to re-parameterize a QAA for estimating IOPs in these waters. We anticipate that the successful re-parameterization and implementation of a QAA for CDOM dominated waters will be widely applicable to many inland and shallow marine and estuarine environments where phytoplankton is not the dominant OAC.

2. Background

2.1. IOP derivation

Several models have been developed to accurately derive the IOPs from the apparent optical properties (AOPs) such as R_{rs} (Maritorena et al., 2002; Lee et al., 2002, 2009). Semi-analytical and QAAs derivation of IOPs is commonly based on the reflectance model shown in Eq. (1) (Gordon et al., 1975, 1988).

$$r_{rs}(\lambda) = \frac{L_u(0^-, \lambda)}{E_d(0^-, \lambda)} = g_1\left(\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}\right) + g_2\left(\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}\right)^2 \quad (1)$$

where, $r_{rs}(\lambda)$ is the remote sensing reflectance just beneath the water surface, $a(\lambda)$ is the spectral total absorption coefficient, $b_b(\lambda)$ is the spectral total backscattering coefficient, $L_u(0^-, \lambda)$ and $E_d(0^-, \lambda)$ are upwelling radiance and downwelling irradiance, respectively, and g_1 and g_2 are geometrical factors.

Based on Eq. (1), several semi-analytical and QAA models have been proposed for deriving the IOPs from ocean waters (Roesler and Perry, 1995; Maritorena et al., 2002; Lee et al., 2002). For inland waters, semi-analytical and QAAs have recently been proposed by Simis et al. (2005, 2007), Li et al. (2012, 2013, 2015), and Mishra et al. (2014). The main difference between semi-analytical and QAA is based on the estimation of $a(\lambda)$ and $b_b(\lambda)$ (Lee et al., 2002). In QAA, the estimation of $a(\lambda)$ does not involve absorption coefficients of individual constituents such as $a_{phy}(\lambda)$, spectral absorption coefficient of non-algal particles ($a_{NAP}(\lambda)$), and spectral absorption coefficient of color dissolved matter (CDM) ($a_{CDM}(\lambda)$). On the contrary, in semi-analytical algorithms (Roesler and Perry, 1995; Maritorena et al., 2002), $a(\lambda)$ is usually estimated by the sum of