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Remote sensing estimation of colored dissolved organic matter (CDOM) in optically shallow waters

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ABSTRACT

It is not well understood how bottom reflectance of optically shallow waters affects the algorithm performance of colored dissolved organic matters (CDOM) retrieval. This study proposes a new algorithm that considers bottom reflectance in estimating CDOM absorption from optically shallow inland or coastal waters. The field sampling was conducted during four research cruises within the Saginaw River, Kawkawlin River and Saginaw Bay of Lake Huron. A stratified field sampling campaign collected water samples, determined the depth at each sampling location and measured optical properties. The sampled CDOM absorption at 440 nm broadly ranged from 0.12 to 8.46 m^{-1}. Field sample analysis revealed that bottom reflectance does significantly change water apparent optical properties. We developed a CDOM retrieval algorithm (Shallow water Bio-Optical Properties algorithm, SBOP) that effectively reduces uncertainty by considering bottom reflectance in shallow waters. By incorporating the bottom contribution in upwelling radiances, the SBOP algorithm was able to explain 74% of the variance of CDOM values (RMSE = 0.22 and R^2 = 0.74). The bottom effect index (BEI) was introduced to efficiently separate optically shallow and optically deep waters. Based on the BEI, an adaptive approach was proposed that references the amount of bottom effect in order to identify the most suitable algorithm (optically shallow water algorithm [SBOP] or optically deep water algorithm [QAA-CDOM]) to improve CDOM estimation (RMSE = 0.22 and R^2 = 0.81). Our results potentially help to advance the capability of remote sensing in monitoring carbon pools at the land-water interface.

1. Introduction

Inland waters (streams, rivers and lakes) are responsible for transporting and transforming large amounts of carbon from terrestrial ecosystems to aquatic environments (Tranvik, 2014). Each year, inland waters emit about 1 gigaton of carbon as CO_2 to the atmosphere and transfer an equivalent amount of carbon to ocean waters (Battin et al., 2009). This flux is larger than originally estimated and more than half of it results from the movement of dissolved organic carbon (DOC) from terrestrial environments (Stedmon et al., 2000). Accordingly, riverine systems (streams and rivers) govern much of the DOC export from terrestrial to aquatic environments (IPCC, 2007) and dictate the spatial and temporal variability of freshwater DOC in drainage watersheds. Shallow coastal and estuarine areas are the primary interface regions for carbon exchange from terrestrial to aquatic ecosystems. The variations of terrestrial carbon exports in these regions are heavily associated with anthropogenic activities (Palmer et al., 2015). Therefore, increased attention is being devoted to carbon monitoring of optically shallow waters. Several studies have demonstrated that remote sensing technologies show great promise for monitoring freshwater DOC dynamics through bio-optical properties (Brezonik et al., 2015; Kutser et al., 2015; Olmanson et al., 2016; Zhu et al., 2015).

Colored dissolved organic matter (CDOM) is defined as the photoactive fraction of dissolved organic matters in water (Brando and Dekker, 2003). Light absorption by CDOM tends to be strongest at short wavelengths (ultraviolet to blue) while diminishing to near zero in the red wavelength region of the electromagnetic spectrum (Markager and Vincent, 2000). So CDOM level is often represented by a CDOM absorption coefficient within the highly absorbed short wavelengths, and 440 nm is frequently used by the remote sensing community (Brando and Dekker, 2003; Matsuoka et al., 2013;

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Menon et al., 2011; Watanabe et al., 2016). Many previous studies have confirmed that CDOM levels are highly correlated to DOC concentrations in coastal & inland waters influenced by river discharge, regulated by terrestrial sources and seasonal effect (Del Castillo et al., 1999; Del Vecchio and Blough, 2004; Ferrari et al., 1996; Hestir et al., 2015; Kowalczuk et al., 2003). Therefore, CDOM is often used as a proxy to trace the spatial distribution of DOC so as to help quantify the transport of terrigenous organic carbon (Mannino et al., 2008). Thus, the quantitative estimation of CDOM absorption via remote sensing aids in the better understanding of carbon cycling at the land-water interface.

Most research efforts on the remote sensing of water biogeochemistry (CDOM, Chl-a and non-algal particles) have focused on the estimation of water bio-optical properties in open oceans (Lee, 2006; Mobley, 1999; Siegel et al., 2002). Generally, many of these remote sensing algorithms empirically utilize band ratios calibrated from regional datasets to retrieve water properties (Kutser et al., 2005; Matthews, 2011). However, they are often site-specific and need intensive calibration when applied to a new environment. Semi-analytical algorithms made a significant improvement to location independence by extracting water biochemical properties based on bio-optical radiative transfer models. Representative algorithms include multi-band quasi-analytical algorithm (QAA) (Lee et al., 2002), Carder-MODIS (Carder et al., 2004), Garver-Siegel-Maritorena (GSM) (Maritorena et al., 2010, 2002), and Linear Matrix (LM) model (Hoge and Lyon, 1996; Yang et al., 2011). Unfortunately, these algorithms cannot separate CDOM absorption from $a_{dg}(440)$, the combined absorption of CDOM and non-algal particles (NAP), due mainly to their similar absorption spectra. Recently, several studies endeavored to extend mainstream ocean color algorithms to derive CDOM absorption for coastal and open ocean waters (Budhiman et al., 2012; Cui et al., 2014; Matsuoka et al., 2013; Shanmugam, 2011; Zhu and Yu, 2013). However, when these relatively mature semi-analytical ocean color algorithms are directly applied to inland waters, the uncertainty of the resulting CDOM estimation is prohibitively high (Zhu et al., 2013b).

In general, there are two major challenges with the current semi-analytical algorithms used for CDOM retrieval of inland waters. First, the bottom effect of shallow freshwater introduces significant uncertainty on CDOM estimation. Ocean color algorithms are developed for optically deep waters, which assume the upwelling water leaving radiance is only the result of water column constituents and ignore bottom reflectance (Stedmon et al., 2000). This assumption is not valid for optically shallow inland and coastal waters, and therefore greatly limits the usage of these algorithms for inland waters (Aitkenhead-Peterson et al., 2003). Specifically, none of the aforementioned algorithms consider the contribution of bottom reflectance and therefore they are not capable of accounting for the high uncertainty introduced by bottom effects in optically shallow waters. Second, semi-analytical algorithms often incorporate empirical parameters into bio-optical models (water radiative transfer models). Such parameters are largely calibrated via ocean and offshore observations. Inland fresh waters are often much richer in water-borne constituents, (i.e., a higher concentration of CDOM, Chl-a and/or suspended sediment), so these algorithms are often not optimal for handling in-land water environments (Zhu and Yu, 2013; Zhu et al., 2013b). Except for a few cases, the majority of published research on CDOM retrieval in optically shallow lake waters adopt empirical methods (Campbell et al., 2011; Kutser et al., 2005, 2015; Odermatt et al., 2012; Olmanson et al., 2016).

Bottom effects have been considered in some aquatic remote sensing studies, including estimating water optical depth (Brando et al., 2009; Majozi et al., 2014; Maritorena et al., 1994; Zhao et al., 2013), retrieval of the diffuse attenuation coefficient (Barnes et al., 2014, 2013; Dekker et al., 2011; Giardino et al., 2015; Volpe et al., 2011), and monitoring bottom sediments properties (Klonowski et al., 2007). All of these approaches include the contribution of bottom sediment reflectance to the total upwelling radiance, which inspired us to develop a CDOM retrieval algorithm for optically shallow waters that also incorporates bottom reflectance.

First, this paper examines *in situ* spectral data and demonstrates the spectral variation in response to water depths. Second, we developed the shallow water bio-optical properties (SBOP) algorithm which incorporates the bottom contribution into a CDOM retrieval algorithm. Third, we investigated the effectiveness of a proposed bottom effect index (BEI) to quickly separate optically shallow and optically deep waters. Finally, an adaptive approach based on our BEI was presented to identify the most suitable algorithm according to varied levels of bottom effect (optically shallow or deep water algorithms) in an effort to reduce overall uncertainty. This study aims to improve the capability of remote sensing to monitor carbon transportation from terrestrial to aquatic ecosystems across broad spatial and temporal scenarios.

2. Method

2.1. Study site

Saginaw Bay in Lake Huron was selected for sampling CDOM levels concurrently with *in situ* remote sensing measurements across a broad range of CDOM levels. The sampling locations encompassed the Saginaw River, Kawkawlin River and inner Saginaw Bay (Fig. 1). The bathymetry ranged from 0.25 to 4 m with a median value of 1.6 m. Generally, the bottom is dominated by sand with intermittent patches of benthic algae (Cladophora) and other aquatic plants. Compared to that of pure sand, the sediments of the lake bottom are relatively dark due to this mixture of the sand and benthic plants. The two rivers mentioned above are of vastly different size and composition and their drainage basins are covered by different dominant vegetation. The Saginaw River is 36 km long with a watershed area of 22,260 km^2. The river has a mean annual discharge of 130 m^3/s (2010–2016). The dominant landcover type is agriculture, which accounts for approximately 52% of the watershed. The Kawkawlin River flows into the Saginaw Bay approximately 1 km north of the Saginaw River mouth. Its length (28 km), discharge and drainage area (647 km^2) are at a significant lower magnitude than those of the Saginaw River. The Kawkawlin River watershed is dominated by deciduous forest (40.2%) with a relatively high percentage of wetland (7.9%).

2.2. Field and laboratory measurements

A total of four cruises were carried out from 2012 to 2015. The cruises covered both spring and autumn seasons: May 7, 2015, May 7, 2013, May 10, 2012 and October 18, 2012. Field sampling design used a spatially stratified method to distribute the sampling locations at several water depth intervals within and near the river plumes; 54 samples were collected (Fig. 1). The sample points were distributed along five transects and sample locations were slightly shifted due to the conditions present on each sampling date. The water depths of 27 sampling locations were measured by a Vexilar® Hand-held Depth Sonar during the cruise on May 7, 2015. The depths of the earlier sampling locations were generated from bathymetry contours downloaded from Michigan Geographic Data Library (MiGDL). These generated depths have been verified by the 2015 field depth measures with a mean error of less than 10%.

Surface water samples and *in situ* spectral data were collected in parallel at each sampling location. Water samples collected were