Remote Sensing of Environment 200 (2017) 352–367

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Hyperspectral remote sensing of shallow waters: Considering environmental noise and bottom intra-class variability for modeling and inversion of water reflectance

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ARTICLE INFO

Keywords:
Bottom intra-class variability
Environmental noise
Maximum likelihood estimation
Radiative transfer model inversion
Shallow water hyperspectral remote sensing
Spectral covariance

ABSTRACT

Hyperspectral remote sensing is now an established tool to determine shallow water properties over large areas, usually by inverting a semi-analytical model of water reflectance. However, various sources of error may make the observed subsurface remote-sensing reflectance deviate from the model, resulting in an increased retrieval error when inverting the model based on classical least-squares fitting. In this paper, we propose a probabilistic forward model of shallow water reflectance variability that describes two of the main sources of error, namely, (1) the environmental noise that includes every source of above-water variability (e.g., sensor noise and rough water surface), and (2) the potentially complex inherent spectral variability of each benthic class through their associated spectral covariance matrix. Based on this probabilistic model, we derive two inversion approaches, namely, MILE (MaxImum Likelihood estimation including Environmental noise) and MILEBI (MaxImum Likelihood estimation including Environmental noise and Bottom Intra-class variability) that utilize the information contained in the proposed covariance matrices to further constrain the inversion while allowing the observation to differ from the model in the less reliable wavebands. In this paper, MILE and MILEBI are compared with the widely used least-squares (LS) criterion in terms of depth, water clarity and benthic cover retrievals. For these three approaches, we also assess the influence of constraining bottom mixture coefficients to sum to one on estimation results.

The results show that the proposed probabilistic model is a valuable tool to investigate the influence of bottom intra-class variability on subsurface reflectance, e.g., as a function of optical depth or environmental noise. As expected, this influence is critical in very optically shallow waters, and decreases with increasing optical depth. The inversion results obtained from synthetic and airborne data of Quiberon Peninsula, France, show that MILE and MILEBI generally provide better performances than LS. For example, in the case of airborne data with depth ranging from 0.44 to 12.00 m, the bathymetry estimation error decreases by about 32% when using MILE and MILEBI instead of LS. Estimated maps of bottom cover are also more consistent when derived using sum-to-one constrained versions of MILE and MILEBI. MILE is shown to be a simple but powerful method to map simple benthic habitats with negligible influence of intra-class variability. Alternatively, MILEBI is to be preferred if this variability cannot be neglected, since taking bottom covariance matrices into account concurrently with mean reflectance spectra may help the bottom discrimination, e.g., in the presence of overlapping classes. This study thus shows that taking potential sources of error into account through appropriate parameterizations of spectral covariance may be critical to improve the remote sensing of shallow waters, hence making MILE and MILEBI interesting alternatives to LS.

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http://dx.doi.org/10.1016/j.rse.2017.08.020
Received 14 December 2016; Received in revised form 26 July 2017; Accepted 14 August 2017

1. Introduction

Optical remote sensing provides an outstanding opportunity to monitor aquatic environments from local to global scales, potentially offering high temporal and spatial resolutions, e.g., as allowed by recent advances in unmanned aerial vehicles or by the Sentinel-2 mission developed by the European Space Agency within the "Copernicus" program (Aschbacher and Milagro-Pérez, 2012; Drusch et al., 2012). The use of such high spatial resolution data (i.e., less than a few dozen meters) is particularly critical for coastal and inland waters, e.g., to map heterogeneous benthic habitats (Mishra et al., 2006; Hedley et al., 2012b), to detect coral bleaching (Andréfouët et al., 2002; Hedley et al., 2012a) or to monitor small lakes and rivers (Joshi and D'Sa, 2015). As compared with the open ocean, coastal and inland waters are generally more complex environments, whose remotely-sensed reflectance may be highly variable due to simultaneous changes in bathymetry, water quality, bottom type, water surface and atmospheric conditions. In shallow waters, the decoupling of these effects has been shown to be more accurate when using hyperspectral data instead of multispectral data (Lee and Carder, 2002; Lee et al., 2013). Indeed, a higher number of spectral bands as well as an increased spectral resolution allow reducing confounding effects between optically-active parameters, e.g., by detecting the subtle changes in reflectance that originate from narrow absorption regions potentially present in bottom albedo (Kutser et al., 2003; Hochberg and Atkinson, 2003; Hedley et al., 2012a; Botha et al., 2013).

In coastal environments, hyperspectral remote sensing methods that allow the simultaneous retrieval of bathymetry, water quality and benthic cover are usually based on a radiative transfer model that describes how light propagates in water (Mobley, 1994). This inverse problem is generally solved using either look-up tables (LUTs) or iterative optimization (Dekker et al., 2011). In the first case, a spectral library corresponding to different combinations of depth, water quality and benthic cover is pre-computed using an exact (Mobley, 1994) or approximated (Lee et al., 1998) radiative transfer model. For each image pixel, the measured reflectance is then matched with the closest simulated spectrum in the LUT. CRISTAL (Comprehensive Reflectance Inversion based on Spectrum matching and TAble Lookup) (Mobley et al., 2005) and ALLUT (Adaptive Linearized Look-Up Trees) (Hedley et al., 2009) as denoted by Dekker et al. (2011) are examples of such approaches. The inverse problem can also be solved by numerically optimizing a cost function that relates measured and simulated reflectance spectra. In this case, the forward model used for simulation has to be sufficiently fast to permit multiple runs for each image pixel. To this end, a number of analytical and semi-analytical models have been developed under various assumptions and water types (Maritorena et al., 1994; Lee et al., 1998; Albert and Mobley, 2003). These models approximate the radiative transfer equation and generally simulate the reflectance of shallow waters as a function of sun-sensor geometry, depth, bottom albedo and water-column inherent optical properties (i.e., absorption and scattering properties of the water column). Note that, whenever possible, the latter can further be related to specific inherent optical properties and concentrations of optically-active water constituents (Brando et al., 2009).

Due to its accurate performance and simplicity, the Euclidean distance has generally been used to assess the goodness-of-fit between the observation and the model, either when using LUTs (Mobley et al., 2005; Hedley et al., 2012a, 2009) or iterative optimization (Lee et al., 2001, 1999; Lee and Carder, 2002; Albert and Gege, 2006; Klonowski et al., 2007; Dekker et al., 2011; Jay et al., 2012; Giardino et al., 2012; Garcia et al., 2014a; McKinna et al., 2015; Jay and Guillaume, 2016). Note that in the case of iterative optimization, the use of Euclidean distance for model inversion corresponds to nonlinear unweighted least-squares fitting. However, this cost function does not fully consider the information contained in the reflectance data. In particular, it does not utilize spectral covariance (i.e., covariance between wavebands), yet such knowledge of the data structure may be useful to improve the retrieval accuracy due to the non-negligible correlation between hyperspectral bands (Gillis et al., 2013).

Importantly, as the least-squares method tries to find the best possible fit between the observation and the model, it is not designed to handle possible deviations between them. For example, the "environmental noise equivalent reflectance difference" (Brando and Dekker, 2003) (hereafter called environmental noise and denoted NEΔr_E) may lead the measured subsurface reflectance to strongly differ from the modeled one. For a given spectral band, NEΔr_E corresponds to the reflectance standard deviation as estimated over an "as homogeneous as possible" water area. As a result, it not only takes into account the sensor noise, but also scene-specific above-water variability, including atmospheric variability, effects related to the rough water surface, refractions of diffuse and direct sunlight, and residuals from imperfect atmospheric, air-water interface and sun glint corrections (Brando and Dekker, 2003; Brando et al., 2009; Botha et al., 2013). To consider such errors within model inversion, Brando et al. (2009) and Botha et al. (2013) have weighted the contribution of each waveband according to the inverse of NEΔr_E. In doing so, the influence of the noisiest and least accurate spectral bands is reduced, which lowers the estimation variance.

Another important source of error between the measured and simulated spectra is the inherent spectral variability of each considered benthic class. Based on PlanarRad simulations and a comprehensive bottom spectral library, Hedley et al. (2012b) have actually demonstrated that this is one of the primary limiting factors for benthic mapping purposes (whereas sensor noise is only a minor factor). Indeed, while a single mean reflectance spectrum is generally used to characterize the spectral response of each benthic class, many authors have shown that such intrinsic variability may sometimes be greater than the mean reflectance itself, either at the local or at the global scales (Hochberg et al., 2003; Mobley et al., 2005; Hedley et al., 2012b; Petit et al., 2017). Therefore, this variability may strongly affect the retrieval accuracy if it is not (or not properly) taken into account during the inversion process. To this end, assuming that the bottom reflectance spectrum only varies according to a single multiplicative factor across all the wavebands, several authors have proposed to estimate this factor for each possible substrate (Lee et al., 1999; Fearns et al., 2011; Garcia et al., 2014b; Petit et al., 2017). Under the same assumption, using the Spectral Angle Mapper (SAM) as a cost function may also decrease the detrimental influence of bottom intra-class variability, since the SAM is insensitive to variations in the global reflectance magnitude (Brando et al., 2009; Botha et al., 2013; Petit et al., 2017). However, this spectral variability cannot always be reliably represented using a single multiplicative factor (Hochberg et al., 2003; Hedley et al., 2012b), thus making the development of alternative inversion methods highly desirable.

In this study, we first propose a realistic probabilistic model of shallow water reflectance variability based on the semi-analytical model of Lee et al. (1998) and that fully describes the influences of environmental noise and bottom intra-class variability. Both sources of error are considered to be Gaussian and characterized by a mean vector and a spectral covariance matrix. Then, using this modeling, we develop two new inversion approaches based on maximum likelihood estimation that enable a pixelwise retrieval of all optically-active parameters, i.e., bathymetry, water clarity parameters and benthic cover. These two approaches are compared with the classical least-squares method using both simulated and airborne data.

2. Data

2.1. Study area

As shown in Fig. 1, the overall study area is located in the Quiberon Bay on the French west coast (around 47°31'N, 3°05'W). Three sites