Remote Sensing of Environment 210 (2018) 307–324

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

An algorithm for optically-deriving water depth from multispectral imagery in coral reef landscapes in the absence of ground-truth data

Jeremy M. Kerr[a],[*], Sam Purkis[b]

[a] Guy Harvey Oceanographic Center, Halmos College of Natural Sciences & Oceanography, Nova Southeastern University, 8000 N Ocean Drive, Dania Beach, FL 33004, USA

[b] CSL - Centre for Carbonate Research, Dept. Marine Geosciences, RSMAS, University of Miami, 4600 Rickenbacker Causeway, Miami, FL 33149, USA

ARTICLE INFO

Keywords:
Bathymetry
Multispectral
Coral reefs

ABSTRACT

Although numerous approaches for deriving water depth from bands of remotely-sensed imagery in the visible spectrum exist, digital terrain models for remote tropical carbonate landscapes remain few in number. The paucity is due, in part, to the lack of in situ measurements of pertinent information needed to tune water depth derivation algorithms. In many cases, the collection of the needed ground-truth data is often prohibitively expensive or logistically infeasible. We present an approach for deriving water depths up to 15 m in Case 1 waters, whose inherent optical properties can be adequately described by phytoplankton, using multi-spectral satellite imagery without the need for direct measurement of water depth, bottom reflectance, or water column properties within the site of interest. The reliability of the approach for depths up to 15 m is demonstrated for ten satellite images over five study sites. For this depth range, overall RMSE values range from 0.89 m to 2.62 m when using a chlorophyll concentration equal to 0.2 mg m^{-3} and a generic seafloor spectrum generated from a spectral library of common benthic constituents. Accuracy of water depth predictions drastically decreases beyond these depths. Sensitivity analyses show that the model is robust to selection of bottom reflectance inputs and sensitive to parameterization of chlorophyll concentration.

1. Introduction

Coupling digital terrain models (DTMs) with benthic habitat classification maps of coral reefs improves our understanding of the environmental mechanisms controlling the development of these landscapes (Brock et al., 2006; Brock et al., 2008; Rankey and Doolittle, 2012; Schlager and Purkis, 2013; Purkis et al., 2014; Wasserman and Rankey, 2014; Harris et al., 2015; Purkis et al., 2015a; Purkis et al., 2015b; Schlager and Purkis, 2015). The production of reliable bathymetric maps from multi- and hyperspectral imagery has received much attention (Lyzenga, 1978; Lyzenga, 1985; Clark et al., 1987; Philpot, 1989; Bierwirth et al., 1993; Sandidge and Holyer, 1998; Lee et al., 1999; Dierssen et al., 2003; Stumpf et al., 2003; Adler-Golden et al., 2005; Albert and Gege, 2006; Conger et al., 2006; Lyzenga et al., 2006; McIntyre et al., 2006; Bills et al., 2007; Mishra et al., 2007; Hogrefe et al., 2008; Brando et al., 2009; Lee et al., 2013; Garcia et al., 2014; Jay and Guillaume, 2014; Ma et al., 2014; Eugenio et al., 2015; Pacheco et al., 2015); however, there is a lack of DTMs for many remote coral reef landscapes due to the absence of the field data necessary to calibrate water depth derivation models. The current study presents a technique for reliably predicting water depth up to 15 m in tropical carbonate landscapes from multispectral satellite imagery without in situ measurements of water depth, scattering and attenuation coefficients for the water column, or bottom reflectance spectra in the target landscape.

For marine areas, subsurface remote sensing reflectance, r_{rs}, is modeled as a combination of the bottom reflectance, ρ_b, and subsurface remote sensing reflectance of optically deep water, r_{rs}^{dp}. By assuming that the downwelling and upwelling diffuse beam attenuation coefficients are equal, r_{rs} can be approximated by (Bierwirth et al., 1993; Philpot, 1989; Maritorena et al., 1994)

$$r_{rs} \approx \frac{\rho_b}{\pi}(e^{-2kz}) + r_{rs}^{dp}(1 - e^{-2kz}) \tag{1}$$

where z is water depth and k is the diffuse beam attenuation coefficient. The latter describes the rate of light attenuation in the water column due to total absorption, a_t, and total backscattering, b_b. This formula forms the basis for many approaches to derive water depth from a multispectral satellite image (Lyzenga, 1978; Clark et al., 1987; Philpot, 1989; Bierwirth et al., 1993; Lyzenga et al., 2006; Lee et al., 2013; Jay and Guillaume, 2014; Eugenio et al., 2015).

---

[*] Corresponding author.
E-mail address: jk908@nova.edu (J.M. Kerr).

https://doi.org/10.1016/j.rse.2018.03.024
Received 3 January 2017; Received in revised form 13 March 2018; Accepted 18 March 2018
0034-4257/ © 2018 Published by Elsevier Inc.

Water depth derivation approaches can be grouped into two broad categories. The first group, physics-based approaches, solve for water depth in Eq. (1) through inversion of the equation or optimization of forward model inputs, such as chlorophyll concentration, gelbstoff concentration, spectral shape, backscattering coefficients, and water depth (Lee et al., 1999; Adler-Golden et al., 2005; Albert and Gege, 2006; Brando et al., 2009; Lee et al., 2013; Garcia et al., 2014; Eugenio et al., 2015). These approaches are more often applied to hyperspectral data rather than multispectral data because the former have finer spectral resolution and additional spectral information, due to the increased number of spectral bands, than the latter. The strength of the physics-based approaches is that they allow for estimation of the physical parameters influencing spectral observations without ground-truth data. However, the complexity of Eq. (1) can be problematic for finding solutions because there exists several unknown parameters for each pixel including the water depth, the bottom reflectance, the water column reflectance, and the diffuse beam attenuation coefficient. While reasonable assumptions of values for the latter two parameters can be made (e.g., Lee et al., 1999, water depth and bottom reflectance still remain unknown for each pixel, and solving for both parameters simultaneously is difficult because multiple combinations of the two values can lead to the same remote sensing reflectance at the water's surface (Lyzenga, 1978; Conger et al., 2006; Lyzenga et al., 2006).

The second group, statistical-based approaches, uses direct observation of water depth within a site to calibrate the predictor coefficients of statistical models that relate water depth to spectral observations (Lyzenga, 1985; Clark et al., 1987; Stumpf et al., 2003; Conger et al., 2006; Lyzenga et al., 2006; Pacheco et al., 2015). The strengths of these approaches is that they avoid some of the difficulties of solving for the unknown parameters in Eq. (1) through the use of statistical regression, and their implementation is more straightforward than a physics-based approach (Stumpf et al., 2003). The primary limitation to these statistical approaches is that field observations are needed to perform the calibration, and for remote locations, such data may be unreliable, sparse, or absent.

The goal of this study is to generate DTMs for remote locations where ground-truth information is absent or limited. To achieve this goal, a hybrid of the physics- and statistical-based methods is developed by combining a 'reef-up' forward model of the water column (Purkis, 2005) with a statistical regression to calibrate the predictor coefficients of a well-known model (Stumpf et al., 2003). A comparison of predicted water depths with ground-truth information for ten satellite scenes over five sites demonstrates the reliability of the approach in predicting depths up to 15 m and the limitations of water depth predictions for areas deeper than 15 m. A sensitivity analysis provides information on model robustness to errors in initial parameterization of chlorophyll concentration and bottom reflectance. The resulting DTMs improve our ability to map the benthic character of remote marine locations for depths shallower than 15 m.

2. Methods

2.1. Overview

The present study uses a combination of satellite imagery, field data, forward modeling, and linear regression to develop a method for water depth derivation and to perform a sensitivity analysis to assess the robustness of the approach. Fig. 1 is a flowchart of our approach, and Table 1 contains a list of the symbols used in this study, their definitions, and their units. In the interest of brevity and clarity, we omit wavelength-dependency in the following equations and provide a brief overview of the equations used for atmospheric correction and forward modeling within the water column.

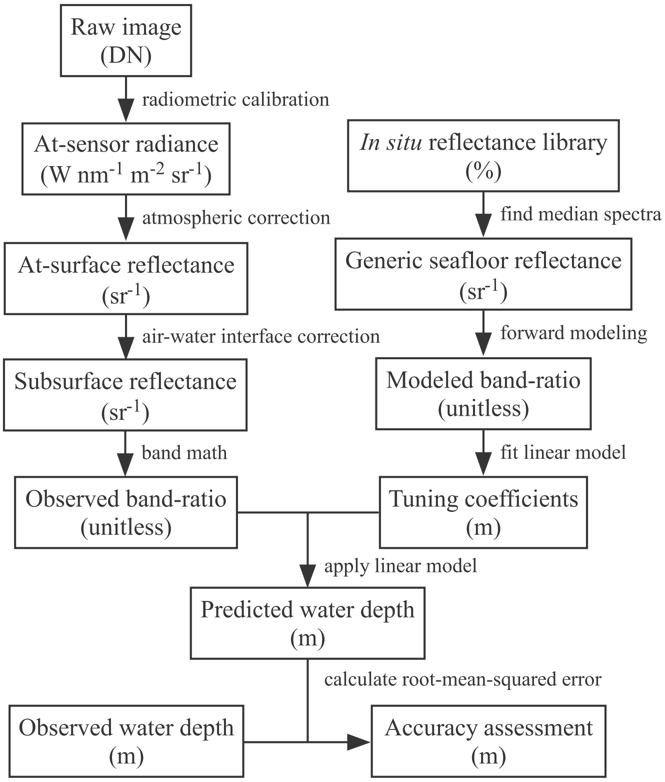

Fig. 1. A flowchart of the approach described in this manuscript. Each box denotes a product, with units in parentheses, and each arrow represents a product-generating process.

Table 1
A list symbols used in this study along with their descriptions and their units.

Symbol	Definition	Units
a_t	Total absorption in the water column	$\mathrm{m^{-1}}$
b_b	Total backscattering in the water column	$\mathrm{m^{-1}}$
$[C]$	Chlorophyll concentration	$\mathrm{mg\ m^{-3}}$
D	Path elongation factor	–
E	Extraterrestrial irradiance	$\mathrm{W\ nm^{-1}\ m^{-2}}$
k	Diffuse beam attenuation coefficient	$\mathrm{m^{-1}}$
L_{atm}	Atmospheric path radiance	$\mathrm{W\ nm^{-1}\ m^{-2}\ sr^{-1}}$
L_{obs}	At-sensor radiance	$\mathrm{W\ nm^{-1}\ m^{-2}\ sr^{-1}}$
n_w	Refractive index of sea water (= 1.34)	–
r_{rs}	Subsurface remote sensing reflectance	$\mathrm{sr^{-1}}$
r_{rs}^{dp}	Subsurface remote sensing reflectance of optically deep water	$\mathrm{sr^{-1}}$
R_{rs}	Above-surface remote sensing reflectance	$\mathrm{sr^{-1}}$
S_i	Spectral response curve of band i	%
t_{dif}	Diffuse transmittance within the atmosphere	–
t_{dir}	Direct transmittance within the atmosphere	–
x	Fine resolution spectral parameter	–
$\overline{x}$	Band-averaged spectral parameter	–
z	Water depth	m
z_{obs}	Observed water depth	m
z_{pred}	Predicted water depth	m
$\beta_{0,1}$	Tuning coefficients	m
θ_0^+	Above-surface solar zenith angle	rad
θ_1^+	Above-surface satellite zenith angle	rad
θ_0^-	Subsurface solar zenith angle	rad
θ_1^-	Subsurface satellite zenith angle	rad
θ'	Incident angle before crossing the air-water interface	rad
θ_t	Transmission angle after crossing the air-water interface	rad
λ	Wavelength	nm
λ_c	Central wavelength of a spectral band	nm
ρ_b	Bottom reflectance	–
ρ_F	Fresnel reflectance	–

Download English Version:

https://daneshyari.com/en/article/8866604

Download Persian Version:

https://daneshyari.com/article/8866604

Daneshyari.com