1. Introduction

Ocean color remote sensing provides synoptic-scale, near-daily observations of marine inherent optical properties (IOPs). Whilst contemporary ocean color algorithms are known to perform well in deep oceanic waters, they often fail operating in optically clear, shallow marine environments where light reflected from the seafloor contributes to the water-leaving radiance. The effect of benthic reflectance in "optically shallow" waters is known to adversely affect algorithms developed for optically deep waters [1, 2]. Whilst adapted versions of optically deep ocean color algorithms have been applied to optically shallow regions with reasonable success [3], there is presently no approach that directly corrects for bottom reflectance using existing knowledge of bathymetry and benthic albedo.

To address the issue of optically shallow waters, we have developed a semi-analytical ocean color inversion algorithm: the Shallow Water Inversion Model (SWIM). SWIM uses existing bathymetry and a derived benthic albedo map to correct for bottom reflectance using the semi-analytical model of Lee et al. [4]. The algorithm was incorporated into the NASA Ocean Biology Processing Group’s L2GEN program and tested in a bathymetrically constrained subregion of the Great Barrier Reef (GBR) in south Florida (Fig. 1). In this paper, we present a comparison between SWIM and two contemporary ocean color algorithms, the Generalized Inherent Optical Property (GIOP) and the Quantiative Algorithm (QAA).

2. Research objectives

• Develop a shallow water inversion algorithm (SWIM) with depth and benthic albedo as inputs

• Evaluate the algorithm performance with radiative transfer modelling study

• Incorporate the algorithm into L2GEN processing software

• Test the algorithm in optically shallow waters of the Great Barrier Reef, Australia

• With the MODIS Aqua time series, compare GIOP and QAA [5, 6] derived using SWIM with values from MODIS

3. Algorithm Structure

SWIM is a forward-inverse type algorithm. A ‘forward’ semi-analytical model [4] is used to simulate sub-surface remote sensing reflectances, rs, which are compared with observed sensor values, rs_o.

The internal parameters (IOPs) of the forward model are dynamically varied using a constrained Levenberg-Marquardt non-linear least squares optimization routine. Once the cost function is minimized (i.e. modelled and observed rs are most similar), SWIM returns the set of IOPs as the ‘inverted’ solution. If convergence to a solution is not achieved, a product failure (PRODFAIL) flag is raised. Previously developed shallow water inversion algorithms sought to derive IOPs, water column depth, and benthic albedo simultaneously [6]. However, such approaches were typically concerned with mapping bathymetry and/or benthic classification using airborne hyperspectral imagery. Conversely, SWIM uses bathymetry and a benthic albedo data as inputs, thereby reducing the number of free parameters in the algorithm. Within this study, an existing high resolution bathymetry [7] map of the Great Barrier Reef has been used. In addition, extensive knowledge of benthic composition [8] has been used to construct a two-class benthic albedo map of ‘light’ and ‘dark’ substrate types.

4. Radiative transfer case study

Hydrolog-EcoLight 5 is a radiative transfer code (HES) [9] used to simulate above-water remote sensing reflectances for both optically deep and shallow situations (20, 15, 10 and 5 m). The simulated IOP data set of IOCCG (2006) [10] was used to parameterize the water column optics, whilst a dark sediment benthic coefficient was used to represent the seafloor. Using SWIM, GIOP and QAA, values of a(443), b(443) and Kd(488) were derived and compared with the actual values. Plots of algorithm-retrieved against actual values are shown in Fig. 2. The results indicate that all three algorithms work well in optically deep waters. However, in shallow, optically clear, shallow waters, GIOP and QAA show distinct positive biases. Conversely SWIM performs well in optically shallow waters. The corresponding regressions statistics indicated that SWIM-derived a(443) and Kd(488) at 20, 15 and 10 m had R-square of 0.92—0.93 and percentage biases (MPB) ranging from 0—7 %. SWIM retrievals of b(443) at 20, 15 and 10 m were also good with R-square and percentage biases ranging from 0.92—0.78 and 0—9 %. At a depth of 5 m, SWIM-derived a(443) and Kd(488) each had R-square of 0.90 and MPB of 14 %. Whilst SWIM-derived b(443) at 5 m had an R-square of 0.61 and an MPB of 28 %. We note that the MPB in GIOP/QAA-derived values of a(443), b(443) and Kd(488) were approximately 30 % at 20 m depth and exceed 100 % at a depth of 5 m.

5. Test region: the Great Barrier Reef

A sub-set of the northern Great Barrier Reef, Australia was used to demonstrate the SWIM algorithm. The clear shallow waters of this region are on average 18 m deep with a mix of benthics comprising sand, seagrasses and corals. Results in Fig. 3 show that for shallow regions (< 20 m) GIOP and QAA give higher values of a(443), b(443) and Kd(488) than SWIM. This is further demonstrated using cross-shelf transects (Fig. 4). The results shows that once a depth of approximately 30 m is reached, SWIM, GIOP and QAA values and GIOP and QAA values show distinct positive biases. Conversely SWIM performs well in optically shallow waters. The corresponding regressions statistics indicated that SWIM-derived a(443) and Kd(488) at 20, 15 and 10 m had R-square of 0.92—0.93 and percentage biases (MPB) ranging from 0—7 %. SWIM retrievals of b(443) at 20, 15 and 10 m were also good with R-square and percentage biases ranging from 0.92—0.78 and 0—9 %. At a depth of 5 m, SWIM-derived a(443) and Kd(488) each had R-square of 0.90 and MPB of 14 %. Whilst SWIM-derived b(443) at 5 m had an R-square of 0.61 and an MPB of 28 %. We note that the MPB in GIOP/QAA-derived values of a(443), b(443) and Kd(488) were approximately 30 % at 20 m depth and exceed 100 % at a depth of 5 m.

6. Time-series comparison

The shallow shelf waters of the region shown in Fig. 3 were selected for analysis using the MODIS Aqua time series (2002—2019). Values of a(443), b(443) and Kd(488) were derived using SWIM, GIOP and QAA from level-1a data and screened for bad values using standard masks and quality control flags. Monthly-averaged data and relative differences were then calculated and are shown in Fig. 5. As expected, SWIM-derived values were consistently lower than GIOP and QAA values through time for the SW region. Differences between SWIM and GIOP/QAA products were overestimated relative to SWIM values. The magnitude of these differences is similar observed in the radiative transfer modelling study.

7. Summary

Here we have demonstrated SWIM, an optically shallow ocean color inversion algorithm. The algorithm is currently incorporated in NASA’s L2GEN processing code and was successfully applied in the Great Barrier Reef, Australia. Radiative transfer modelling and comparisons between SWIM and GIOP/QAA indicate the algorithm performs as expected in both deep and shallow waters. SWIM has the potential to enhance research and management of sensitive shallow water environments by complementing existing systems for monitoring water quality and ecosystem health. Further, because SWIM is based on a proven LIDAR processing code it is easily applicable to sensors other than MODIS Aqua and regions outside the Great Barrier Reef.

8. Future work

• Validation and fine tuning of the SWIM algorithm using in situ datasets

• Implementing a tide offset correction procedure

• Extending the SWIM algorithm to other regions with well characterized bathymetry/benthos

• Potential to incorporate SWIM into L2GEN’s generalized IOP algorithm framework

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