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An assessment of Landsat-8 atmospheric correction schemes and remote sensing reflectance products in coral reefs and coastal turbid waters

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ABSTRACT

The Operational Land Imager (OLI) onboard Landsat-8 satellite can provide remote sensing reflectance (R_{rs}) of aquatic environments with high spatial resolution (30 m), allowing for benthic habitat mapping and monitoring of bathymetry and water column optical properties. To facilitate these applications, accurate sensor-derived R_{rs} is required. In this study, we assess atmospheric correction schemes, including NASA's NIR-SWIR approach, Acolite's NIR and SWIR approaches and the cloud-shadow approach. We provide the first comprehensive evaluation for Landsat-8 R_{rs} retrievals in optically shallow coral reefs, along with an investigation of Landsat-8 R_{rs} products in a temperate turbid embayment. The obtained Landsat-8 R_{rs} data products are evaluated with concurrent *in situ* hyperspectral R_{rs} measurements. Our analyses show that the NASA and the cloud-shadow approaches generated reliable R_{rs} products across shallow coral reefs and optically deep waters. This evaluation suggests that high quality R_{rs} products are achievable from the Landsat-8 satellite in optically shallow environments, which supports further application of Landsat-8 type measurements for coral reef studies.

1. Introduction

Aquatic biodiversity and environmental science have entered a new era with the availability of advanced ocean color remote sensing imagers (Turner et al., 2015). Among many other remote sensors, such as those operated by NASA, NOAA, USGS and ESA, Landsat-8 satellite is the continuation mission to its predecessors with coverage of coastal ecosystems (Loveland and Irons, 2016; Roy et al., 2014). The Operational Land Imager (OLI) onboard Landsat-8 can provide remote sensing reflectance (R_{rs}, sr^{-1}) of aquatic environments with high spatial resolution (30 m), allowing the monitoring of aquatic ecology and associated environmental parameters (*e.g.*, Andréfouët et al., 2001; Olmanson et al., 2008; Palandro et al., 2008). Currently, quantitative evaluation of Landsat-8 R_{rs} products in optically diverse aquatic environments, particularly of shallow waters including coral reefs, is rare. Non-validated Landsat-8 R_{rs} products limit their applicability and introduce unknown uncertainties in aquatic ecology and water quality studies in coastal environments.

The OLI instrument is equipped with four visible bands (443, 482, 561 and 655 nm) and has improved signal-to-noise ratios (SNR) (Schott et al., 2016) and radiometric calibration (Markham et al., 2014). Thus it has the potential to retrieve R_{rs} products with a higher quality compared to its predecessors. Retrieval of R_{rs} products from ocean color satellites requires an atmospheric correction (AC) algorithm (IOCCG, 2010). Existing operational AC schemes were primarily developed for clear oceanic waters (Gordon and Wang, 1994), where the assumption of zero water-leaving radiance (L_w, μW $\mathrm{cm}^{-2}\,\mathrm{sr}^{-1}\,\mathrm{nm}^{-1}$) at the near-infrared (NIR) bands is valid (a.k.a. “black pixels”). For more turbid waters, a combination of NIR and shortwave-infrared (SWIR) bands are used to select the aerosol types (Wang and Shi, 2007), with any non-negligible L_w derived with an iterative approach (Bailey et al., 2010) through NASA's SeaDAS processing software (Franz et al., 2015). Acolite is another radiative transfer (RT)-based AC system (Vanhellemont and Ruddick, 2014, 2015). Both SeaDAS and Acolite systems can be used for atmospheric correction of Landsat-8 Level-1 measurements. In addition, some *ad hoc* AC approaches have been developed and applied that utilize radiative transfer-based codes such as 6S model (Giardino et al., 2014). Further, image-based models have also shown promise to aid atmospheric correction for both optically shallow and deep environments (Amin et al., 2014; Lee et al., 2007; Zhang et al., 2017). Despite the wide spectrum of available AC schemes, the performance of these algorithms in optically shallow waters is rarely evaluated. It remains uncertain which AC scheme can deliver reliable R_{rs} products from Landsat-8 measurements in various water bodies.

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The R_{rs} products of operational ocean color satellites (*e.g.*, MODIS Aqua and SNPP VIIRS) are usually validated through dedicated efforts with the use of radiometrically and spectrally accurate *in situ* R_{rs} matchups retrieved within a short period of time from an overpass (± 3 h) (Hlaing et al., 2014; Mélin et al., 2007; Zibordi et al., 2009b). However, the lack of *in situ* matchup data hinders the validation of the Landsat-8 R_{rs} products. Among the earlier efforts, Zheng et al. (2016) presented a dozen *in situ* and Landsat-8 R_{rs} matchups in an extremely turbid lake but with the matchup time relaxed to ± 6 h; a large time window might contribute significantly to the differences observed between field and satellite data. Pahlevan et al. (2016) provided some preliminary results of Landsat-8 R_{rs} data in Boston Harbor but focused on the Acolite scheme. With the Ocean Color Aerosol Robotic Network (AERONET-OC) (Zibordi et al., 2006) data, Pahlevan et al. (2017) further evaluated the performance of the AC schemes implemented in SeaDAS and reported that a combination of the 865 nm and 2201 nm bands provided generally better R_{rs} products. Although the Landsat-8 products can be "cross-validated" with other available ocean color satellite products (Qiu et al., 2017), the data quality of the reference data used therein is often underdetermined. To date, Landsat-8 R_{rs} products are rarely evaluated in optically shallow environments, despite the important value of Landsat-8 imagery in shallow water remote sensing (Lymburner et al., 2016; Pacheco et al., 2015). The earlier qualitative assessments of Landsat-8 R_{rs} retrievals were limited by available matchup data (Giardino et al., 2014; Yadav et al., 2017). Considering these existing issues and challenges with data product validations, it is critical that the performance of Landsat-8 be thoroughly assessed with accurate *in situ* matchups for a wide range of nearshore waters.

Our objective is to quantitatively assess the performance of existing AC schemes for Landsat-8 in coral reefs and turbid water environments that include NASA's standard NIR-SWIR approach (Franz et al., 2015), the Acolite approach (Vanhellemont and Ruddick, 2014, 2015), and the cloud-shadow approach (CSA) (Lee et al., 2007). To our best knowledge, this is the first comprehensive evaluation of Landsat-8 R_{rs} retrievals in optically shallow coral reef waters. All R_{rs} retrievals are validated with concurrent high-quality *in situ* measurements of hyperspectral R_{rs} spectra (within ± 1.5 h of overpass). We demonstrate that the NASA and the cloud-shadow approaches generate the most reliable R_{rs} retrievals across shallow coral reefs and optically deep waters. It is confirmed that the Landsat-8 instrument can indeed provide high quality R_{rs} measurements for optically shallow waters.

2. Data and methods

2.1. Study areas

The *in situ* radiometric measurements for this effort were conducted in a broad range of aquatic environments. They include the optically shallow coral reef environments of La Parguera Natural Reserve, Puerto Rico (Fig. 1A), Maui, Hawaii (Fig. 1B), and Florida Keys (Fig. 1C). The La Parguera Natural Reserve has the most extensive coral reef ecosystem in Puerto Rico as well as a coastal mangrove fringe, mangrove islands and seagrass meadows (Pittman et al., 2010). The patch reefs consist mostly of hard and soft corals (Fig. 2A), with abundant seagrasses on the shallow back-reef lagoons (Fig. 2B). The water depths vary from ~1 m up to 20–30 m at the shelf edge. The chlorophyll *a* concentrations (CHL, $\mathrm{mg\,m^{-3}}$) at these sites are ~0.2–0.3 $\mathrm{mg\,m^{-3}}$ (Otero and Carbery, 2005). The southwest coasts of Maui have abundant fringe corals with diverse species, which are under great environmental pressures (Prouty et al., 2017; Rodgers et al., 2015). Our measurements in Maui were obtained from 15 sites distributed in Kahekili, Launiupoko and Olowalu areas, where the natural coral formations provide a canopy of hard corals (Fig. 2C and Fig. 2D) that are structurally complex with water depths varying from ~1 m to 10 m. These Maui stations are characteristic of extremely clear waters, with CHL as low as ~0.15 $\mathrm{mg\,m^{-3}}$ (Wedding et al., 2018). Four stations were measured in the coral reefs of Florida Keys with water depths ranging from 3 to 7 m, where the CHL varies around 0.3–0.6 $\mathrm{mg\,m^{-3}}$.

The waters of Massachusetts Bay (Fig. 1D) are usually strongly stratified in summer and autumn, but various factors, including tides, winds, and buoyancy gradients affect water properties and their distributions. The chlorophyll *a* concentrations in these relatively turbid waters are on average ~1.5 $\mathrm{mg\,m^{-3}}$. Boston Harbor is a tide-dominated environment with contributions from several major rivers that include the Charles River, Mystic River and Neponset River. The waters have annual average concentrations of suspended particulate matter (SPM) varying from 3 to 8 $\mathrm{mg\,l^{-1}}$ and CHL from 2 to 5 $\mathrm{mg\,m^{-3}}$ (Taylor, 2016).

2.2. *In situ* hyperspectral remote sensing reflectance and data reduction

A total of 13 field trips were conducted between July 2013 and October 2017, coinciding with Landsat-8 satellite overpasses (Table 1). During each field campaign, a downward-looking hyperspectral ocean color radiometer (HyperOCR, Satlantic Inc.) attached with a skylight-blocking apparatus (SBA) was used to directly measure the water-leaving radiance, while an upward-looking hyperspectral radiometer (HyperOCR, Satlantic Inc.) was employed to measure the downwelling plane irradiance (E_d, $\mathrm{\mu W\ cm^{-2}\,nm^{-1}}$). The two radiometers were calibrated over the spectral domain between ~350–800 nm, with a spectral interval of 3 nm (FWHM 10 nm) and a radiometric calibration uncertainty of < 2.5% for radiance and 1.5% for irradiance (Voss et al., 2010). The SBA system measures L_w with small uncertainty (refer to Section 4.1) and high accuracy by blocking the light from the sky reflected off the water surface (Lee et al., 2013). In addition, a depth sounder was integrated to simultaneously measure water depths. A GPS sensor and an underwater high definition (HD) camera were also attached to provide coordinates (± ~3 m precision) and images of bottom substrates, respectively.

To reduce the R_{rs} measurement uncertainty, the following protocol was adopted. First, the radiance and irradiance sensors were installed on two extended arms (30 cm long) so as to minimize the disturbance of the buoy (Fig. 2, Wei et al., 2015; https://www.osapublishing.org/oe/abstract.cfm?uri=oe-23-9-11826). The instrument package floated on the water's surface and simultaneously measured both E_d and L_w and depth for a period of 3–5 min. The instrument was also kept at a distance > 20 m from the small operation boat to avoid boat disturbance to the measurements. The raw data were calibrated to absolute radiometric units with the manufacturer's data processing software PROSOFT. The hyperspectral E_d measurements were then interpolated so that both E_d and L_w have exactly the same wavelengths. Both spectral E_d and L_w were further used to derive the instantaneous remote sensing reflectance (Wei et al., 2015), as

$$R_{rs}(\lambda,t)=\frac{L_w(\lambda,t)}{E_s(\lambda,t)} \tag{1}$$

with t for the observation time. The $R_{rs}(\lambda,t)$ data with instrument inclination > 5° were filtered out. To identify and filter-out potentially contaminated data points due to the radiometric system occasionally submerged in water or the SBA popped up in air, the following procedures were further developed and employed. First, the probability density function (PDF) of the $R_{rs}(\lambda,t)$ data sequence at a red band (usually 698 nm) was calculated with the Matlab® normal kernel smoothing function, ksdensity, at 100 equally spaced points that cover the range of the $R_{rs}(698,t)$ data. Then all $R_{rs}(\lambda,t)$ spectra with $R_{rs}(698,t)$ exceeding ± 15% of its mode were removed. The mean $R_{rs}(\lambda)$ spectrum was then derived from the remaining $R_{rs}(\lambda,t)$ spectra. For measurements from Massachusetts Bay and Boston Harbor, the self-shading errors were corrected with the scheme specifically developed for the SBA system (Shang et al., 2017). No appropriate shade correction algorithm is available for shallow water measurements; nonetheless, the self-shading errors in coral reefs are small due to the strong contributions from bottom reflectance.