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Detection of surface algae blooms using the Sentinel 2A: An algorithm of the best strip ratio for a freshwater lake

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Abstract

Harmful Algal Blooms (HABs) are problematic algal blooms that cause toxicity and associated environmental impacts on freshwater, marine and coastal ecosystems. HABs produce strong toxins that pose a threat to humans and wildlife, with significant negative impacts i.e., food web vectoring, airborne toxic events, decay of algal blooms resulting in low oxygen or hypoxia and killing fish and birds. Measurement of algae concentrations has conventionally relied on direct water sampling for lab-based cell enumeration. These traditional approaches are extremely labor-intensive, tedious, and limited spatially and temporally. Remote sensing (RS) based methods are capable to handle these complications in inland and near-coastal waters (consistent revisit rate for well-structured time series analyses, regular and reliable observations over a large area). The Multispectral Instrument (MSI) onboard European Space Agency's (ESA) Sentinel 2 satellite initiates a new era in high-to-moderate resolution (10, 20, 60 m) of earth observation data. Sentinel 2A (S2A) satellites launched in 2015 as a part of the ESA's Copernicus program. S2A filter-based push-broom imager, measures the reflected solar spectral radiances in 13 spectral bands ranging from the visible-near infrared (VNIR) (0.4422-0.8640 µm) to the short-wave infrared (SWIR) (0.9432-2.1857 µm) bands. This study aims to develop a method to estimate Chlorophyll-a (Chl-a) concentration in freshwater lake waters using in situ data of Chl-a, water reflectance, and contemporaneous S2A imagery over the Kotmale reservoir Sri Lanka.

1. Introduction

Algae are neither homogenous organisms, nor belong to natural taxonomic grouping. They are eukaryotic organisms that has permanent plastid, Chl-a as their primary photosynthetic pigment (Granéli and Turner, 2006). Algae are unicellular prokaryotes, their growth is driven by light, nutrient (nitrate and phosphates) and temperature. These organisms are primary producers; produce food via photosynthesis and key foundation of marine and freshwater food chains and webs (Klemas, 2012). Freshwater ecosystems provide unique habitats, supports high level of biodiversity. These ecosystems occupy approximately 0.8% of the Earth's surface but support almost 6% of all known species, i.e., more than 10, 000 fish species live in freshwaters, which is about 40% of the global fish species. Moreover, these freshwater ecosystems provide irreplaceable goods and services. Inland lakes, rivers are among the most threatened freshwater ecosystems on the Earth. Besides, biodiversity losses in freshwaters are much faster or even worse (Xiong et al., 2020).

HABs are ubiquitous (Clark et al., 2017; Liang et al., 2017; Torbick and Corbiere, 2015), posing serious threats to marine and freshwater aquatic ecosystems and causes significance health consequences. HABs are an issue in marine, brackish, and freshwater systems. Large and tiny lakes, reservoirs, rivers, ponds, dugouts, and wide selection of other surface waters were affected worldwide. HABs and toxic algae kill fish and birds, food web vectoring, airborne toxic events, decay of algal blooms resulting in low oxygen or hypoxia, impede visual predators, attenuate light to submerged aquatic vegetations, distress in humans resulting respiratory

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irritations, breathing difficulties, and even mortality (Xu et al., 2019; Palacios et al., 2017).

Microcystis aeruginosa is considered as a Cyanobacterial HAB organism which impede recreational use of waterbodies, reduce esthetics, lower dissolved oxygen concentration and cause taste and odor issues in drinking water. They also produce microcystins (MC-LR) which are powerful hepatotoxins. Long-term exposure to MC-LR causes development of liver cancer and liver tumors under low-level exposer (Metcalf et al., 2018; Palacios et al., 2017). Yet not all cyanobacterial genera are toxic. Different cyanobacteria produce similar toxins i.e., *Microcystis* sp, *Anabaena* sp, and *Anabaenopsis* sp all have been capable of producing microcystin (Torbick and Corbiere, 2015). Furthermore, cyanobacterial toxins also implicated among the factors contributing to chronic kidney disease of uncertain etiology in Sri Lanka. Thus, presence of cyanobacterial harmful algal bloom formation in freshwaters is a serious concern (Kulasooriya, 2017).

HABs are extremely patchy, they often remain unobserved by current monitoring programs, and spatial and temporal frequencies of conventional water sampling programs are not adequate to report changes in phytoplankton biomass, bloom conditions. Conventional in situ sampling and laboratory measurements comprise of physicial, chemicial and biologicial properties and indicators. Though, the in situ measurements of water quality parameters only represent point estimates of water quality conditions in time and space nevertheless, obtaining spatial-temporal variations in large waterbodies are almost impossible, conventional methods are extremely labor-intensive, tedious, monitoring and forecasting of entire waterbodies might be unapprochable, due to water surface extent and toporgaphic characteristics (Gholizadeh et al., 2016; Ouma et al., 2018).

RS become an effective tool to derive the spatial and temporal behavior of aquatic ecosystems (Liang et al., 2017; Neil et al., 2019). Combination of RS with conventional in situ sampling methods coupled with laboratory measurements and analysis may provide effective approach (Bonansea et al., 2018). Numerous algorithms have been developed to estimate Chl-a concentrations. Namely, Sea-viewing Wide Field-of-view Sensor (SeaWiFS), Moderate Resolution Imaging Spectroradiometer (MODIS), Medium-spectral Resolution Imaging Spectrometer (MERIS), Sentinel 2 and 3, Landsat Operational Land Imager (OLI) and Enhanced Thematic Mapper Plus (ETM+) which are spaceborne missions that have been frequently used in deriving the information on Chl-a concentrations.

Chl-a taken as the index of phytoplankton abundance, and may result in visible changes in water bodies. HABs have distinct spectral characteristics i.e., significant absorption bands around 500 nm, 675 nm and reflectance peaks 550 nm, and 700 nm; which is caused due to dramatic increase of phytoplankton biomass. When a HAB dominates the phytoplankton biomass, Chl-a concentration has the advantage of providing an estimate of the total concentration of the bloom (Kutser, 2004).

2. Method

The datasets in this research include S2A satellite imagery of Kotmale reservoir, Sri Lanka acquired on July 21, 2020, approximately at 05:06 GMT. Level -1C MSI data downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus) provided by European Space Agency. Water samples at 45 study points were collected randomly. Coordinates for water sample stations were recorded using a global positioning system (GPS). The in-situ data and corresponding satellite image pixels were used to develop and evaluate the supervised learning method for retrieval of the Chl-a concentration in the lake.

2.1. Laboratory Analysis of Chlorophyll-a

Chl-a quantification, used to estimate the total phytoplankton biomass, was carried out according to the Lorenzen, 1967 method. Each sample was filtered using 0.8 µm pore size filters under vacuum pressure that were then kept frozen at 253.15K for 8-12 hours in darkness. Chl-a was extracted from these filters in methanol by ultrasonication and agitation. The extracts were centrifuged at 13300 rpm for 10 minutes to reduce the turbidity. The Chl-a concentration of the extracts was determined spectrophotometrically using a Labomed UV-VIS RS spectrometer. Chl-a concentration was calculated accordingly.

2.2. Atmospheric Correction

Removing the intervening atmosphere effect from S2A satellite imagery is vital for the accurate estimation of Chl-a concentration in the reservoir. In this research, the Rayleigh correction is carried out to obtain the Rayleigh-corrected reflectance. The reflectance to radiance results from the below formula:

$$L_{TOA}(\lambda) = \frac{Q_{cal} \quad E(\lambda) \quad cos\vartheta_i}{\pi \quad d^2} \qquad (1)$$

Where LTOA(λ) is Rayleigh adjusted radiance (Wm-^{2}sr-1), Qcal is the pixel value, θi is the incidence angle (radians), E(λ) mean solar irradiance for each band (Wm-^{2}) and d is the sun-earth distance in astronomical units (AU). For Sentinel 2 the incidence angel is substituted with the values from the sun zenith band θs.

Undetected clouds can produce misleading results in the analysis of surface and atmospheric parameters. Water color RS products requires reliable cloud detection and cloud shadow detection and classification before atmospheric correction. The SHIMEZ method assumes that clouds are grey to white. Assumption is made that the mean of the red, blue, and green bands greater than a defendable threshold (B) (0.25), and that the difference between each of two bands lower than a pre-determined threshold (A) (0.15 over the day).

2.2.1. Algorithms for Chlorophyll-a

All available band ratios, frequently used for Chl-a estimation were assessed in this study, including two blue-green band ratios (B1/ B3 and B2/B3, respectively) one green-red band ratio (B3/B4), two NIR-red band ratios (B5/ B4 and B6/B4, respectively) one NIR-Red three-band ratio ((B5 + B6) /B4) and Normalized Difference Chlorophyll Index (B4-B6/B4+B6).

2.2.2. Quantifying the Quality of Predictions

Standard statistical metrics were used to evaluate the empirical model to estimate Chl-a in the reservoir. The Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Mean Absolute Percentage Error (MAPE) metrics were used.

3. Results

All cross-regression analyses between Chl-a and sensor radiance that corresponds to the band ratios shown in Table 1 and Table 2 including the locations under semitransparent clouds and cloud shadows.

Table 1. Performance of selected Chlorophyll-a estimation algorithms and results of the best-fit curve analyses

S2A band ratio	Regression equation coefficients $\ln Y = \beta_0 + \beta_1 x$	
	β_0	β_1
B1/B3	17.5	-12.6
B2/B3	21.2	-18.0
B3/B4*	-36.8	22.3
B5/B4	-22.7	24.6
B6/B4	-10.9	7.7
B5+B6/B4	-15.7	6.5
B4-B6/B4+B6	-3.3	18.6

Table 2. Selected Chlorophyll-a estimation algorithms and results of the best-fit curve analyses for in situ measurements of Chlorophyll-a located under semitransparent clouds and cloud shadows

S2A band ratio	Regression equation coefficients $Y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$			
	β_0	β_1	β_2	β_3
B1/B3	-2105.9	4421.6	-3090.8	719.4
B2/B3	-9827.0	23674.9	-19007.1	5085.2
B3/B4*	-927.7	1775.4	-1133.0	241.12
B5/B4	1762.6	-5470.8	5659.6	-1951.4
B6/B4	457.5	-1162.9	98.3	-277.4
B5+B6/B4	1592.4	-2227.4	1038.0	-161.6
B4-B6/B4+B6	1.9	75.3	954.6	3857.5

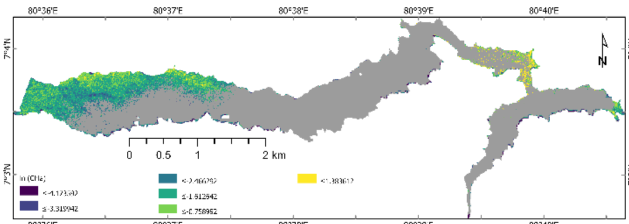

Figure 2. Chl-a retrieved from S2A MSI (B3/B4 Exponential curve fitted) in Kotmale reservoir. Areas covered with semitransparent clouds and cloud shadows are masked in color gray

The summarized statistical analyses of the S2A MSI derived Chl-a concentrations over the locations including study points under semitransparent cloud cover are listed in Table 3 and Table 4 respectively.

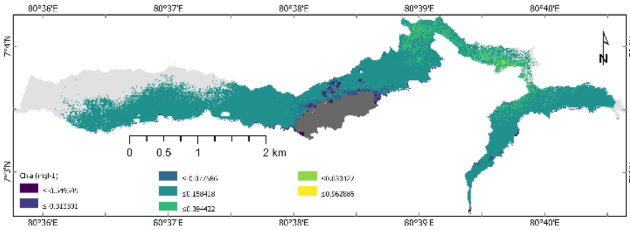

Figure 3. Chl-a retrieved from S2A MSI for study points under the semitransparent cloud and loud shadows (B3/B4 Polynomial curve fitted) in Kotmale reservoir. Dense clouds and cloud shadows are masked in dark gray.

Table 3. Validation of Sentinel 2A band ratio models considering RMSE, NRMSE and MAPE

S2A band ratio	RMSE	NRMSE	MAPE
B1/B3	0.180	0.454	0.534
B2/B3	0.190	0.478	0.853
B3/B4*	0.092	0.233	0.255
B5/B4	0.149	0.374	0.914
B6/B4	0.167	0.422	0.749
B5+B6/B4	0.163	0.410	0.799
B4-B6/B4+B6	0.167	0.421	0.758

Table 4. Validation of S2A band ratio models considering RMSE, NRMSE and MAPE for in situ measurements located under semitransparent clouds

S2A band ratio	RMSE	NRMSE	MAPE
B1/B3	0.154	0.591	12.696
B2/B3	0.091	0.349	2.019
B3/B4*	0.055	0.213	3.142
B5/B4	0.116	0.447	6.167
B6/B4	0.120	0.463	6.167
B5+B6/B4	0.120	0.463	6.554
B4-B6/B4+B6	0.110	0.421	6.022

4. Discussion

Evaluation on the performances of frequently used band ratio algorithms for estimating Chl-a in Kotmale reservoir, demonstrated the appropriateness of green-red two band ratio to estimate Chl-a in the reservoir using S2A data. The cross-relationship of Chl-a and band ratios for non-cloudy locations, with the strongest correlation, was detected between under exponential curve fit of Chl-a and band ratio of B4/B4. Measurements located under clouds and cloud shadows show a correlation with Chl-a and band ratio of B3/B4 under polynomial fit.

5. Conclusion

The main aim of this study was to evaluate the suitability of S2 MSI imagery for mapping lake water quality parameters (Chl-a) by means of band ratio type algorithms, which has demonstrated good performance in previous water color remote sensing studies.

The clouds' interference can cause lowering of the signal to noise ratio of reflectance, especially in blue and green bands, which were used to calculate the calibrated spectral radiance, which might be problematic for predicting low spectral band ratio derived Chl-a in the study points which are located under clouds and cloud shadows.

The second prominent reflectance peak around 700 nm occurred because of minimal absorption of water constituents i.e., Chl-a, Colored Dissolved Organic Matter (CDOM), non-algal particles (NAP) and particulate backscattering, which controls the reflectance variations in this region. While the peak magnitude; near 700 nm vs. Chl-a concentration indicated a very poor relationship, the increase in the Chla concentration caused the displacement of the peak position in the red region which is usually observed in turbid and productive waters. The NIR-Red band ratio algorithms did not result in a significant improvement in performance relative to the green-red two band ratio model feasibly because of the effect of absorption by CDOM NAPs.

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