SATELLITE DERIVED ESTIMATION OF CHLOROPHYLL-A ON HARMFUL ALGAL BLOOMS (HABS) IN SELECTED DAMS OF VHEMBE DISTRICT, LIMPOPO PROVINCE

LINTON F. MUNYAI[1*], FARAI DONDOFEMA[1], KAWAWA BANDA[2], MULALO I. MUTOTI[3] & JABULANI R. GUMBO[3]

[1]Aquatic Systems Research Group, Department of Geography and Environmental sciences, University of Venda, South Africa

[2]Integrated Water Resources Management Centre, C/O Department of Geology, University of Zambia, Zambia

[3]Department of Earth Sciences, University of Venda, South Africa

ABSTRACT

Satellite remote sensing techniques have been proved to be capable of quantifying chlorophyll-a (Chl-*a*) levels by estimating algal concentrations in water bodies. Harmful algal blooms (HABs) pose a significant threat to many water bodies in South Africa. This study aimed at using a remote sensing solution to estimate chlorophyll concentrations in water bodies of Vhembe District Municipality using Landsat 8 OLI. This study seeks to provide quantitative water quality information for the Vhembe region's water bodies from a time series of satellite remotely sensed data and in-situ laboratory data. The 30 meters spatial resolution multispectral Landsat 8 OLI for 2016, 2017 and 2018 were used to derive Chl-*a* estimate at three water bodies, namely, Nandoni, Albasini and Vondo reserviors. The Chl-*a* concentrations obtained from Landsat 8 (OLI) satellite were compared with the laboratory analysis using the Kappa coefficient statistical analysis. This study show that Landsat derived chl-*a* estimates have a high positive correlation of 80–90% accurate with field measurements. In all the reservoirs, it was detected that there is low content of HABs and thus the water bodies are in good condition since the chl-*a* concentrations were very low. In conclusion, it can be stated that Landsat 8 OLI sensor can be used to map and monitor inland water bodies dominated by algal blooms to a certain extent.

Keywords: chlorophyll-a, harmful algal blooms, L andsat 8-OLI, remote sensing, water quality.

1 INTRODUCTION

Anthropogenic activities progressively subject the freshwater ecosystems to stress, which significantly decreases the water quality, and this reduces chances for aquatic life (Rashid and Romshoo, 2013). Most of the freshwater resources are threatened by harmful algal blooms (HABs) which increases in severity within developing countries (Vilmi et al., 2015). These HABs often tend to alter aquatic habitats, through shading, reducing dissolved oxygen and can also pose adverse effects on various life stages of fish and other pelagic marine organisms (Stumpf and Tomlinson, 2007). Remote sensing has been used previously to monitor these phenomena (Winarso and Ishizaka, 2017). Previous studies conducted on assessing the Spatio-temporal distribution of HABs mostly were primarily done in larger reservoirs and marine systems (Carvalho et al., 2010; Kudela et al., 2015); however, with advancement, remote sensing can now utilize data sets and statistical regressions techniques to analyze reflectance from an inland water body (Diouf, and Seck, 2019; Hikosaka and Noda, 2019; De Souza et al., 2020). Within South Africa, HABs cause mass fatalities of fish and other aquatic species in aquatic systems (Botes et al., 2003). The Spatio-temporal distribution of HABs on inland aquaculture especially in Vhembe District, has not been studied. Furthermore, HABs are increasingly attracting the attention of water authorities, environmental agencies and government departments since they pose water quality and treatment problems (Kutser et al., 2006). This study evaluated the distribution extent of HABs along the water supply reservoirs

ISSN: 2398-2640 (paper format), ISSN: 2398-2659 (online), http://www.witpress.com/journals

DOI: 10.2495/EI-V5-N4-362-374

of the Vhembe region in the Limpopo Province. It estimated the chl-a concentration of the respective reservoirs.

Fish kills have occurred for many years, possibly from cyanobacteria toxins that have been ingested by fish while feeding on floating diets which are passively assimilated through gills during breathing (Dawood et al., 2015). Most algae species are considered helpful in food-fish production ponds (Zimba et al., 2001) They release oxygen as by-product of photosynthesis process and remove toxic compounds from a water column such as ammonia and nitrates (Huang et al., 2018). Inland fisheries contribute to economic development, poverty alleviation and food security whereas on the other side they degrade the quality of water resources (McCafferty et al., 2012). According to Craig et al. (2017), fish feeds contribute to degradation of water quality in food-fish production ponds. The evidence suggest that eutrophic conditions lead to increasing dominance of HABs which pose threat to aquatic ecosystems through producing potentially lethal cyanotoxins (Paerl et al., 2016).

According to Trescott (2012), HABs in surface waters such as lakes and ponds results from the impacts of anthropogenic and natural activities. Nutrients loads in surface waters also contribute to the increased growth of HABs in our water bodies. It is essential to essentially blooms in freshwater systems to provide knowledge, indicators of degraded water quality in different areas, and different other alerts on the progression of HABs in our water resources (Adeleye et al., 2016). Since water treatment is expensive and costly in most rural areas, there is a cost-effective, to monitor the growth of HABs using remote sensing in the water for management purposes (Lawton and Robertson, 1999).

1.1 Harmful algal blooms, chlorophyll-A and remote Sensing

Remote sensing has widely been used in monitoring HABs in lakes, oceans and dams. However, few studies have focused on remote sensing monitoring cyanobacteria in inland aquaculture water bodies by extrapolating algae, phycocyanin and chl-a present. Remote sensing application for HABs detection requires satellite sensors with high spatial/temporal resolution and high radiometric sensitivity (Giardino et al., 2014). According to Shen et al. (2012), remote sensing of monitoring HABs requires knowledge, skills and a comprehensive understanding of remote sensing mechanisms. Caballero et al. (2020) suggest that monitoring of HABs using remote sensing as a tool is more complicated, however, satellite remote sensing of monitoring inland water bodies impacted with HABs is limited to larger water bodies/lakes and handheld sensors because there are few satellite sensors with high spatial resolution to map inland water bodies since they are small (Kutser, 2009).

Most studies focused on chl-a estimation in turbid water using different algorithms, models and laboratory analysis of chl-a concentration (Hansen et al., 2013; Hansen et al., 2015; Caballero et al., 2013). Several studies on detection and monitoring chl-a in water bodies are based on the empirical models of reflectance, radiance in narrow bands and chl-a (Devi et al., 2015). Researchers collected field data on chlorophyll through handheld satellite or sensors mounted on space to validate their models. This is a very good approach since satellites remote sensing data is calibrated or validated by field observation and ground truthing. Furthermore, the combination of all these methods makes the data more linked and as such, the results are reliable and conclusive.

One of the main objectives of aquaculture systems especially in rural area is to provide food security and alleviate poverty by provision of employment to people. Numerous studies reported fish mortality in aquaculture systems from cyanobacterial toxins and oxygen competition (Zimba et al., 2001; Zi et al., 2018). Most fish farming is vulnerable to deterioration by HABs and this is influenced by different environmental factors (physical, biological and chemical) which are driven by anthropogenic activities. It is of paramount importance to reduce the impacts of HABs in fish farming hence this study intends to investigate the use of satellites and in-situ field data as a tool for monitoring the progression of HABs.

Remote Sensing can be used to determine chlorophyll and cyanobacteria contents in deep and shallow waters. The concentration of chl-a in water bodies has been determined using the empirical correlation between radiance and reflectance of algae in water bodies, thus few studies focused on narrow bands (Duab et al., 2012; Devi et al., 2015). Other studies developed models focusing on both empirical and semi-analytical algorithms for conducting in-situ spectral analysis (Ali et al., 2014; Mouw et al., 2015). Most of the field data which are collected in remote sensing studies are intended to validate models formulated, however some of the data is used to correlate the two sets of data (Satellite and in-situ data). It has been found that in-situ field measurements provide the water bodies spectrum and chl-a concentration through collection of water samples and analyzing spectral reflectance from Spectroradiometer. Several studies have been done in determination of chlorophyll and its derivatives with exceptions of pheophytin and phycocyanin in natural water systems by extracting the pigment from the plant material or the algal bloom (Gavrilović et al., 2012; Hynstova et al., 2018). Moreover, lot of methodology in determination of chlorophyll has been identified by researchers including the use of satellite remote sensing in extracting the green pigment found on algae by estimating chlorophyll content.

In detecting trophic status of chl-a, mathematical algorithms have been used with the application of top-atmosphere data from satellite especially MERIS (Gons et al., 2005; Odermatt et al., 2010; Zhang et al., 2019; Free et al., 2020). Matthews et al. (2012) used Maximum Height Peak (MPH) algorithm to detect cyanobacterial blooms, surface scums and chl-a by calculating the height of the dominant peak across the MERIS bands which are red and near infrared between 664 and 885nm wavelength. The idea of using both MERIS and in situ data was to allow models to cover a wide trophic water dominated by surface scums, where oligotrophic, hypertrophic and dry floating algae are differentiated based on the MPH variable magnitude (Matthews et al., 2012). Hence the current study applied Landsat 8-OLI in detecting the distribution of HABs at Nandoni, Albasini and Vondo dams. The present study aimed at (1) determining the spatial and temporal distribution of chl-a in Nandoni, Vondo and Albasini dam, (2) to compare the remote sensing data and in-situ data through applying the existing model of remote sensing on inland water bodies.

2 MATERIAL AND METHODS

2.1 Study area

Three reserviors, namely, Nandoni, Albasini and Vondo in Vhembe District Municipality (VDM) were considered for in-situ sampling of chl-a analysis using both Laboratory and Remotely sensed methods (Fig. 1). Two reserviors (Nandoni and Vondo) are located under Thulamela Local Municipality and Albasini Dam is located under Makhado Local Municipality. All these reserviors are the water suppliers of almost all communities in VDM and they provide habitat to most fish, invertebrates and other aquatic species. Nandoni reservior (Lat: −22.983324° and Long: 30.579191°) is the most reliable water supply reservoir and is situated at Ha-Budeli which is 30 km from Thohoyandou town. The reservoir supplies water to different communities such as Thohoyandou, Sibasa, University of Venda and nearby communities. The reservoir has the total capacity of 164 million cubic meters and a catchment area of 1380 km^3 with the total surface area of 1570 hectares.

Vondo reservior (Lat: −22.946375° and Long: 30.336539°) is situated at the mountainous area under Vondo Tribal authority. The reservoir is a source of water to communities such as Thathe Vondo village, Gondeni, Maranzhe and Phiphidi and has the total capacity of 30 million cubic meters with 219 hectares of surface area. Whereas Albasini reservior (Lat: −23.107238° and Long: 30.117978°) is a source of water for communities such as Makhado town, Mpheni Village, Elim and Waterval. This reservoir has a total capacity of 25,200,000 cubic meters and a surface area of 350 hectares.

Sampling sites were selected to span the entire surface of each reservoir. Sampling station quantity was determined for them to provide enough representation of the entire water body including both deep and shallow areas (Randolph et al., 2008). The samples were collected along the water column at a range of 0.5–1.0 m in the morning at each site of the dam and stored on ice for analysis in the laboratory. Nineteen (19) samples were collected from Nandoni dam and eight (8) Samples were collected from Vondo dam whereas (nine) 9 samples were collected from Albasini dam using a boat. The number of collected samples in each dam depended on the size of the particular reservoir.

2.2 Chlorophyll-A analysis in water samples

Water samples were defrosted, homogenized in an electric homogenizer and filtered through a Whatman GF/F 0.7 μm glass fiber filter papers, and the volume of the filtered samples was recorded. A 90% ethanol solution was used to extract the chl-a and concentration in mg/m^3 were measures using the spectrophotometric method and converted to μg/L. Absorbance was measured at 665 and 750 nm using a spectrophotometer (Orion aquamate 700, VIS

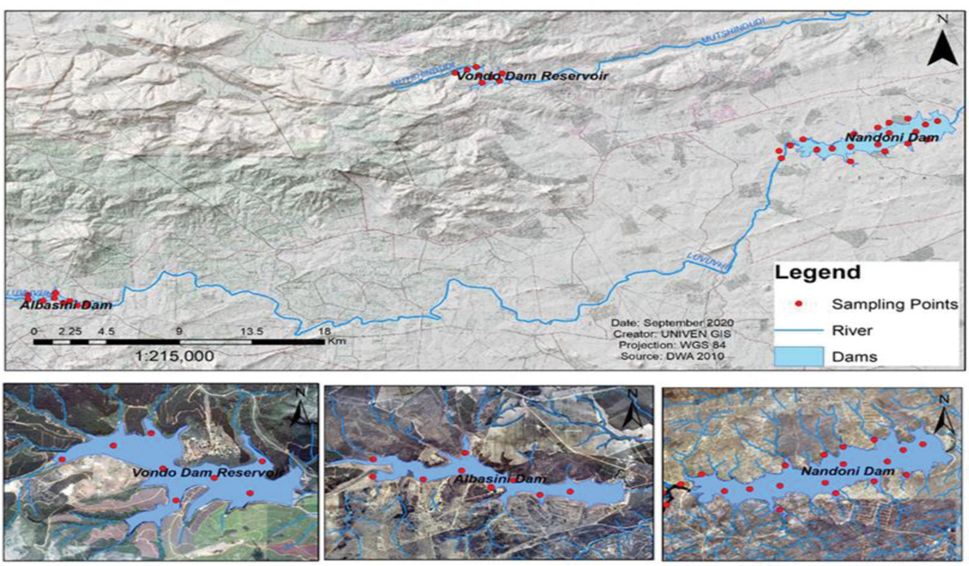

Figure 1: Map of the study area where Measurements of Chlorophyll-a in the dams for comparison with Satellite data were done.

spectrometer). Water samples that were collected during summer and winter were analyzed in the laboratory for chl-a concentration. Chl-a calculation was performed by subtracting absorbance 665a-750a = corrected 665a, absorbance 665b-750b = corrected 665b absorbance. In the present study, the Spectro-photometrical method was employed as described by Dalu et al. (2013) for analysis of chl-a in water samples. The equation 1 below was used to calculate the concentration of chl-a in water samples:

$$Chl-a = \frac{29.62\left(665a-665b\right)\times Ve}{Ve\times l} \tag{1}$$

Where: V_e = Volume of ethanol extract (ml)
Vs = Volume of water sample filtered (litres)
l = Path length of cuvette (cm)

2.3 Remote sensing data acquisition and pre-processing

Three medium spatial resolution (30 m) multispectral Landsat 8 Operational Land Imager (OLI) images freely acquired over Nandoni, Vondo and Albasini for the year 2016, 2017 and 2018 were used to derive chl-a estimates from the selected points in the reservoirs. In this study, all images with cloud cover greater that 75% were excluded to retrieve chl-a concentration accurately (Ndungu et al., 2013). The satellite images were acquired on the following dates (Table 1):

All Landsat images were downloaded from USGS and were in Digital number format (DN values). To derive chl-a from those images, the images were calibrated from DN values to Top-of-atmosphere spectral reflectance units (Wm-2 sr-1 μm-1) using the algorithm provided by the USGS for converting reflective band to top-of-atmosphere reflectance. The algorithm (2) is as follows:

$$\rho\lambda = M\rho Qcal + A\rho \tag{2}$$

Where: $M\rho$ = Reflectance_Mult_Band
$A\rho$ = Reflectance_Add_Band
Qcal = Quantized and calibrated standard product pixel values (DN)

All the variables presented on the above equation could be retrieved from the metadata file which was downloaded with the original images. Band math was also used to convert radiance to reflectance using ENVI 4.4 Software. The visible spectral bands of the Landsat OLI (Band 2 and 3) were used in order to retrieve chl-a over the Nandoni, Albasini and Vondo reservoirs (Dube, 2012; Dube et al., 2014).

Table1: Landsat acquisition information sourced from USGS ONLINE Archive (http://earthexplorer.usgs.gov/.).

Satellites images	**Date of acquisitions**	**Landsat scene ID**	
2016	26 August 2016	LC81690762016223LGN01	**Path= 169**
2017	26 August 2017	LC81690762017241LGN00	**Row= 76**
2018	26 August 2018	LC81690762018228LGN01	

In estimating chl-a concentrations from reflectance values, spectral bands at 445 and 556nm are very important because that is where chl-a absorption is at peak while the lowest chl-a absorption is normally found at 520 and 550 nm (Dube, 2012; Dube et al., 2014). Based on this knowledge, this study employed the most popular chl-a estimation expression (Yadav et al., 2019; Buditama et al., 2017) to derive estimates over Nandoni, Albasini and Vondo dam from atmospherically corrected Landsat OLI images. The following function (3) was used to computes chl-a concentration:

$$\text{Log Chl-a} = (2.41*\text{B4}/\text{B3}) + 0.187 \tag{3}$$

2.4 Data validation

The chl-a in-situ data that were measured in the field on the 07 September 2017 was used to validate the Landsat 8 OLI which was acquired on the 26 of August 2017. The data was validated by comparing the concentrations of chl-a of two different dates in all reservoirs. The concentrations of chl-a for both field measurements and remotely sensed data were exported from ESRI ArcGIS 10x attribute table to Microsoft excel spreadsheet.

Kappa coefficient statistic method was used for validating the field measurements and the pixel values retrieved from Landsat 8. Kappa measured inter-raster agreement for the two data sets collected and K value was computed using Microsoft excel. Equation 4 below was used to determine the significance of two variables which had a strong relationship. After deploying the above index, an output was created on ENVI software 4.4 with a Logarithm spectral reflectance value, therefore an anti-log was calculated.

$$K = \frac{\text{Po} - \text{Pc}}{1 - \text{Pc}} \tag{4}$$

Where, Po = Field measurements
Pc = Remotely sensed values (Derived from anti-log expression)
K= Agreement Coefficient Value

3 RESULTS AND DISCUSSION

3.1 Remote sensing and in-situ measurements

Figure 2 shows the maps of chlorophyll-*a* concentration estimated by the model where red and green band ratios were used. On this study, we had shown the potential of estimating chlorophyll-*a* concentration in dams with the positive pixel values. The pixels were not represented in the maps, but the classes represented on the images were derived from the empirical model used by Buditama et al. (2017).

From the image classes shown on Fig. 2, 2016 Images in all reservoirs showed very low concentration of chl-*a*, however Landsat 8 OLI was able to map algal blooms in the respective reservoirs. In the reservoirs, distribution of chl-*a* varies spatially and temporally. It can simply be observed that during summer 2016, the concentration of chl-*a* was very low as compared to summer 2018 at Nandoni reservoir. However, the algal abundance was remotely sensed at the edges of the dam. From the observation of the images in Fig. 2, spatial distribution of low algal content was observed in the middle of the Nandoni reservoir in the year

2018 while in 2016 there were no algal blooms detected. Vondo reservoir revealed no algal bloom content from 2016 to 2018. This shows that Vondo reservoir has not been impacted by cyanobacterial blooms for the period of 3 years. The concentration of chl-*a* in Vondo reservoir ranged from 0.0 to 0.3 mg m^{-3}.

In Nandoni and Albasini reservoirs, the chl-*a* had higher values on the area near the dam wall and reservoir edges while getting lower in the middle of the reservoir. This statement is based on sample data P9, P11, P17 and P19 which are nearest samples to the edges and in the middle of the reservoir. The dominance of chl-*a* is mainly caused by the few nutrients which are washed from agriculture, mining and other industries and deposited on the edges of the reservoirs. This results in a rapid growth of algae where there is high accumulation of nutrients (at the edges of the dams). The temporal variations of chl-*a* concentrations are mainly caused by rainfall which tempers with runoff as the main supplier of algal blooms (Buditama et al., 2017).

From Fig. 2, it was also observed that besides detection of algal blooms in water, during classification, vegetation adjacent to the reservoir was detected as algae since plants contains the chlorophyll pigment, however, the present study only accounts for chl-*a* detected within the water body as attested by the field measurements.

Overall, from the results obtained from the remotely sensed and the In-situ measurements, it can be concluded that the three reservoirs have not been affected by high concentration of chlorophyll between the year 2016 and 2018. Since all the data discussed in this study was acquired during summer periods with low rainfall, this maybe the reason for low chlorophyll concentration in the dams because of low rainfall which normally carry nutrients to the water bodies which facilitate algal growth.

From the remotely sensed and Laboratory analysis, we have observed a strong correlation of pixel values derived from chl-*a* estimates and chl-*a* values analyzed in the laboratory (Tables 2 to 4). The correlation is positive because the increase in one value of chlorophyll estimates from Landsat is an increase in the Lab data while decrease of Landsat pixel value is also a decrease in Chlorophyll lab results. This study demonstrated the potential of Landsat 8

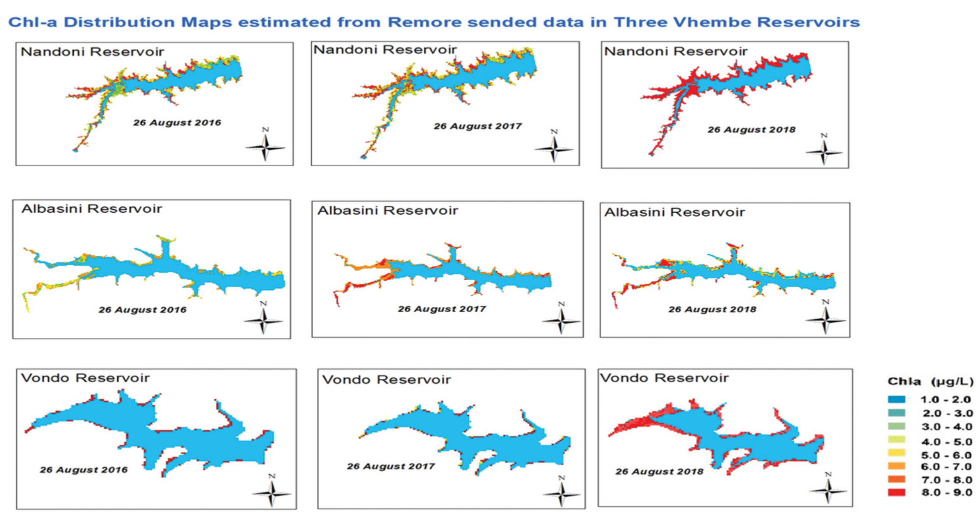

Figure 2: Showing chlorophyll-a distribution map in the Nandoni, Albasini and Vondo dams in Vhembe district, Limpopo province.

Table 2: Mean Concentrations of chlorophyll-a for Laboratory analysis, remotely sensed data and KAPPA Index Value in Nandoni dam for three years (2016, 2017 and 2018.).

Sample number (Nandoni Dam)	Field measurements. Chlorophyll-a concentration (mg m^{-3})	Remotely sensed (Anti-Log extracted values)	KAPPA Index value
P1	0.8	0.2	0.75 (75%)
P2	0.8	0.2	0.75 (75%)
P3	0.9	0.5	0.80 (80%)
P4	0.7	0.1	0.67 (67%)
P5	0.8	0.5	0.60 (60%)
P6	0.3	0.2	0.13 (13%)
P7	0.8	0.3	0.71 (71%)
P8	0.9	0.1	0.89 (89%)
P9	0.8	0.3	0.71 (71%)
P10	0.7	0.1	0.67 (67%)
P11	0.8	0.2	0.75 (75%)
P12	0.7	0.1	0.67 (67%)
P13	0.7	0.1	0.67 (67%)
P14	0.6	0.5	0.20 (20%)
P15	0.9	0.5	0.80 (80%)
P16	0.8	0.2	0.75 (75%)
P17	0.9	0.5	0.80 (80%)
P18	0.7	0.1	0.67 (67%)
P19	0.8	0.6	0.50 (50%)

Table 3: Mean Concentrations of chlorophyll-a for Laboratory analysis, remotely sensed data and KAPPA Index Value in Vondo dam for three years (2016, 2017 and 2018.).

Sample number (Vondo Dam)	Field measurements. Chlorophyll-a concentration (mg m^{-3})	Remotely sensed (Anti-Log extracted values)	KAPPA Index value
V1	0.9	0.1	0.89 (89%)
V2	0.9	0	0.90 (90%)
V3	0.8	0	0.80 (80%)
V4	0.8	0.2	0.75 (75%)
V5	0.7	0.1	0.67 (67%)
V6	0.8	0	0.80 (80%)
V7	0.9	0.5	0.80 (80%)
V8	0.9	0.4	0.83 (83%)
V9	0.7	0.2	0.63 (63%)

Table 4: Mean Concentrations of chlorophyll-a for Laboratory analysis, remotely sensed data and KAPPA Index Value in Albasini dam for three years (2016, 2017 and 2018.).

Sample number (Albasini Dam)	Field measurements. Chlorophyll-a concentration (mg m^{-3})	Remotely sensed (Anti-Log extracted values)	KAPPA-Index value
A1	0.9	0.5	0.80 (80%)
A2	0.8	0.1	0.78 (78%)
A3	0.8	0.2	0.75 (75%)
A4	0.9	0.5	0.80 (80%)
A5	0.7	0.1	0.67 (67%)
A6	0.6	0.4	0.33 (33%)
A7	0.9	0.1	0.89 (89%)
A8	0.9	0.4	0.83 (83%)
A9	0.9	0.2	0.88 (88%)

OLI images on mapping areas with high and low concentration of chl-*a*. The spatio-temporal variation in the concentration of Chl-*a* within the dams likely reflects the yearly and physicochemical factors influences. Chlorophyll estimates of all dams derived from Landsat OLI images were very low for most part of the dams which is attributed to decreased water level in the Nandoni, Vondo and Albasini dam (Dalu et al., 2015).

4 CONCLUSION

Based on the derived and measured total chl-a concentrations across all the reservoir i.e. Nandoni, Vondo and Albasini, it can be concluded that the dams possess low concentrations. The algorithm employed in the images to derive chl-a worked successfully on the Landsat OLI images. It can be concluded that Landsat OLI is suitable for real time monitoring of HABs in water bodies and can accurately map areas where cyanobacterial blooms are abundant. This was also attested by the Kappa coefficient analysis which determined the level of agreements between two or more data sets. 80–90% of K values were observed across all the sites which showed high level of agreement of correlation of field chl-a concentration and satellite remotely sensed variables.

ACKNOWLEDGEMENTS

This research was funded by National Research Foundation of South Africa “NRF Innovation Master’s scholarship”, project UID 106618 and University of Venda Post graduate research funds: Grant number SES/07/ERM/01. We wish to acknowledge Dr Sam Kaheru for providing a working space for conducting experiments in the School of Education, Physical Science Laboratory, University of Venda.

REFERENCES

[1] Adeleye, A.S., Conway, J.R., Garner, K., Huang, Y., Su, Y. & Keller, A.A., Engineered nanomaterials for water treatment and remediation: costs, benefits, and applicability. *Chemical Engineering Journal*, **286**, pp. 640-662, 2016.

[2] Ali, K., Witter, D. and Ortiz, J., Application of empirical and semi-analytical algorithms to MERIS data for estimating chlorophyll a in Case 2 waters of Lake Erie. *Environmental Earth Sciences*, **71(9)**, pp. 4209-4220, 2014.

[3] Botes, L., Smit, A.J. and Cook, P.A., The potential threat of algal blooms to the abalone (Haliotis midae) mariculture industry situated around the South African coast. Harmful Algae, **2(4)**, pp. 247-259, 2003.

[4] Buditama, G., Damayanti, A. and Pin, T.G., December. Identifying Distribution of Chlorophyll-a Concentration Using Landsat 8 OLI on Marine Waters Area of Cirebon. In *IOP Conference Series: Earth and Environmental Science* (Vol. 98, No. 1, p. 012040), 2017. IOP Publishing.

[5] Caballero, I., Fernández, R., Escalante, O.M., Mamán, L. and Navarro, G., New capabilities of Sentinel-2A/B satellites combined with in situ data for monitoring small harmful algal blooms in complex coastal waters. *Scientific Reports*, **10(1)**, pp. 1-14, 2020.

[6] Carvalho, G.A., Minnett, P.J., Fleming, L.E., Banzon, V.F. and Baringer, W., Satellite remote sensing of harmful algal blooms: A new multi-algorithm method for detecting the Florida Red Tide (Karenia brevis). Harmful algae, **9(5)**, pp. 440-448, 2010.

[7] Craig, S., Helfrich, L.A., Kuhn, D. and Schwarz, M.H., Understanding fish nutrition, feeds, and feeding. 2017.

[8] Dalu, T., Clegg, B. and Nhiwatiwa, T., Temporal variation of the plankton communities in a small tropical reservoir (Malilangwe, Zimbabwe). *Transactions of the Royal Society of South Africa*, **68(2)**, pp. 85-96, 2013.

[9] Dalu, T., Dube, T., Froneman, P.W., Sachikonye, M.T., Clegg, B.W. and Nhiwatiwa, T., An assessment of chlorophyll-a concentration spatio-temporal variation using Landsat satellite data, in a small tropical reservoir. *Geocarto International*, **30(10)**, pp. 1130-1143, 2015.

[10] Dawood, M.A., Koshio, S., Ishikawa, M. and Yokoyama, S., Effects of partial substitution of fish meal by soybean meal with or without heat-killed Lactobacillus plantarum (LP20) on growth performance, digestibility, and immune response of amberjack, Seriola dumerili juveniles. *BioMed research international*, 2015, 2015.

[11] De Souza, R., Grasso, R., Peña-Fleitas, M.T., Gallardo, M., Thompson, R.B. and Padilla, F.M., Effect of Cultivar on Chlorophyll Meter and Canopy Reflectance Measurements in Cucumber. *Sensors*, **20(2)**, pp. 509, 2020.

[12] Devi, L. & Ohno, M., Effects of BACE1 haploinsufficiency on APP processing and Aβ concentrations in male and female 5XFAD Alzheimer mice at different disease stages. Neuroscience, **307**, pp. 128-137, 2015.

[13] Diouf, D. and Seck, D., Modeling the Chlorophyll-a from Sea Surface Reflectance in West Africa by Deep Learning Methods: A Comparison of Multiple Algorithms. arXiv preprint arXiv:1912.03216, 2019.

[14] Duan, H., Ma, R., Xu, J., Zhang, Y. and Zhang, B., Comparison of different semi-empirical algorithms to estimate chlorophyll-a concentration in inland lake water. *Environmental monitoring and assessment*, **170(1)**, pp. 231-244, 2010.

[15] Dube, T., Primary productivity of intertidal mudflats in the Wadden Sea: a remote sensing method. [Msc Thesis] University of Twente Faculty of Geo-Information and Earth Observation (ITC), 2012.

[16] Dube, T., Gumindoga, W. & Chawira, M., Detection of land cover changes around Lake Mutirikwi, Zimbabwe, based on traditional remote sensing image classification techniques. *African Journal of Aquatic Science*, **39(1)**, pp. 89-95, 2014.

[17] Free, G., Bresciani, M., Pinardi, M., Ghirardi, N., Luciani, G., Caroni, R. and Giardino, C., A regional evaluation of the influence of climate change on long term trends in chlorophyll-a in large Italian lakes from satellite data. *Earth System Dynamics Discussions*, pp. 1-19, 2020.

[18] Gavrilović, B., Popović, S., Ćirić, M., Subakov–Simić, G., Krizmanić, J. and Vidović, M., Qualitative and quantitative composition of the algal community in the water column of the Grlište reservoir (Eastern Serbia). *Botanica Serbica*, **40(2)**, pp. 129-135, 2016.

[19] Giardino, P.P., Karnnike, K., Masina, I,. Raidal, M & Strumia, A. The universal Higgs fit. Journal of High Energy Physics. Springer Berlin Heidelberg, 2014.

[20] Gons, H.J., Rijkeboer, M. and Ruddick, K.G., Effect of a waveband shift on chlorophyll retrieval from MERIS imagery of inland and coastal waters. *Journal of Plankton research*, **27(1)**, pp. 125-127, 2005.

[21] Hansen, C., Swain, N., Munson, K., Adjei, Z., Williams, G. P. & Miller, W., Development of sub-seasonal remote sensing chlorophyll-a detection Models. American Journal of Plant Sciences, 2013, 2013.

[22] Hansen, C.H., Williams, G.P. & Adjei, Z., Long-Term Application of Remote Sensing Chlorophyll Detection Models: Jordanelle Reservoir Case Study. *Natural Resources*, **6**, pp. 123-129, 2015.

[23] Hikosaka, K. and Noda, H.M., Modeling leaf CO2 assimilation and Photosystem II photochemistry from chlorophyll fluorescence and the photochemical reflectance index. *Plant, cell & environment*, **42(2)**, pp. 730-739, 2019.

[24] Huang, J., Zhang, Y., Huang, Q. and Gao, J., When and where to reduce nutrient for controlling harmful algal blooms in large eutrophic lake Chaohu, China?. *Ecological Indicators*, **89**, pp. 808-817, 2018.

[25] Hynstova, V., Sterbova, D., Klejdus, B., Hedbavny, J., Huska, D. and Adam, V., Separation, identification and quantification of carotenoids and chlorophylls in dietary supplements containing Chlorella vulgaris and Spirulina platensis using high performance thin layer chromatography. *Journal of pharmaceutical and biomedical analysis,* **148**, pp. 108-118, 2018.

[26] Kudela, R.M., Palacios, S.L., Austerberry, D.C., Accorsi, E.K., Guild, L.S. and Torres-Perez, J., 2015. Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters. *Remote Sensing of Environment*, **167**, pp. 196-205.

[27] Kutser, T., Metsamaa, L., Strömbeck, N. and Vahtmäe, E., Monitoring cyanobacterial blooms by satellite remote sensing. Estuarine, *Coastal and Shelf Science*, **67(1-2)**, pp. 303-312, 2006.

[28] Kutser, T., Passive optical remote sensing of cyanobacteria and other intense phytoplankton blooms in coastal and inland waters. *International Journal of Remote Sensing*, **30(17)**, pp. 4401-4425, 2009.

[29] Lawton, L.A. & Robertson, P.K.J., Physico-chemical treatment methods for the removal of microcystins (cyanobacterial hepatotoxins) from potable waters. School of Applied Sciences, The Robert Gordon University, St Andrew Street, Aberdeen, UK. *Chemical Society Reviews*, **28**, pp. 217–224, 1999.

[30] Matthews, M.W., Bernard, S. and Robertson, L., An algorithm for detecting trophic status (chlorophyll-a), cyanobacterial-dominance, surface scums and floating vegetation in inland and coastal waters. *Remote Sensing of Environment*, **124**, pp. 637-652, 2012.

[31] McCafferty, J.R., Ellender, B.R., Weyl, O.L.F. and Britz, P.J., The use of water resources for inland fisheries in South Africa. *Water SA*, **38(2)**, pp. 327-344, 2012.

[32] Mouw, C.B., Greb, S., Aurin, D., DiGiacomo, P.M., Lee, Z., Twardowski, M., Binding, C., Hu, C., Ma, R., Moore, T. and Moses, W., Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions. *Remote sensing of environment*, **160**, pp. 15-30, 2015.

[33] Ndungu, J., Monger, B.C., Augustijn, D.C., Hulscher, S.J., Kitaka, N. & Mathooko, J. M., Evaluation of spatio-temporal variations in chlorophyll-a in Lake Naivasha, Kenya: remote-sensing approach. *International journal of remote sensing*, **34(22)**, pp. 8142-8155, 2013.

[34] Odermatt, D., Giardino, C. and Heege, T., Chlorophyll retrieval with MERIS Case-2-Regional in perialpine lakes. *Remote Sensing of Environment*, **114(3)**, pp. 607-617, 2010.

[35] Paerl, H.W., Gardner, W.S., Havens, K.E., Joyner, A.R., McCarthy, M.J., Newell, S.E., Qin, B. and Scott, J.T., Mitigating cyanobacterial harmful algal blooms in aquatic ecosystems impacted by climate change and anthropogenic nutrients. *Harmful Algae*, **54**, pp. 213-222, 2016.

[36] Randolph, K., Wilson, J., Tedesco, L., Li, L., Pascual, D.L. and Soyeux, E., Hyperspectral remote sensing of cyanobacteria in turbid productive water using optically active pigments, chlorophyll-a and phycocyanin. *Remote Sensing of Environment*, **112(11)**, pp. 4009-4019, 2008.

[37] Rashid, I. and Romshoo, S.A., Impact of anthropogenic activities on water quality of Lidder River in Kashmir Himalayas. *Environmental monitoring and assessment*, **185(6)**, pp. 4705-4719, 2013.

[38] Shen, L., Xu, H. & Guo, X. Satellite remote sensing of harmful algal blooms (HABs) and a potential synthesized framework. *Sensors*, **12(6)**, pp. 7778-7803, 2012.

[39] Stumpf, R.P. and Tomlinson, M.C., *Remote sensing of harmful algal blooms. In Remote sensing of coastal aquatic environments*, Springer: Dordrecht, pp. 277-296, 2007.

[40] Trescott, A., Remote Sensing Models of Algal Blooms and Cyanobacteria in Lake Champlain. Environmental & Water Resources Engineering Masters Projects. University of Massachusetts Amherst. Paper 48., 2012.

[41] Vilmi, A., Karjalainen, S.M., Landeiro, V.L. and Heino, J., Freshwater diatoms as environmental indicators: evaluating the effects of eutrophication using species morphology and biological indices. *Environmental monitoring and assessment*, **187(5)**, pp. 243, 2015.

[42] Winarso, G. and Ishizaka, J., Validation of cochlodinium polykrikoides red tide detection using seawifs-derived chlorophyll-a data with nfrdi red tide map in south east korean waters. *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, **14(1)**, pp. 19-26, 2017.

[43] Yadav, S., Yamashiki, Y., Susaki, J., Yamashita, Y. and Ishikawa, K., Chlorophyll estimation of lake water and coastal water using landsat-8 and sentinel-2a satellite. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, 2019.

[44] Zi, J., Pan, X., MacIsaac, H.J., Yang, J., Xu, R., Chen, S. & Chang, X. Cyanobacteria blooms induce embryonic heart failure in an endangered fish species. Aquatic Toxicology, **194**, pp. 78-85, 2018.

[45] Zimba, P.V., Khoo, L., Gaunt, P.S., Brittain, S. and Carmichael, W.W., Confirmation of catfish, Ictalurus punctatus (Rafinesque), mortality from Microcystis toxins. *Journal of Fish Diseases*, **24(1)**, pp. 41-47, 2001.

[46] Zhang, F., Li, J., Shen, Q., Zhang, B., Tian, L., Ye, H., Wang, S. and Lu, Z., A soft-classification-based chlorophyll-a estimation method using MERIS data in the highly turbid and eutrophic Taihu Lake. *International Journal of Applied Earth Observation and Geoinformation*, **74**, pp. 138-149, 2019.