Physics and Chemistry of the Earth 127 (2022) 103193

Contents lists available at ScienceDirect

Physics and Chemistry of the Earth

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

Remotely sensed data for estimating chlorophyll-*a* concentration in wetlands located in the Limpopo Transboundary River Basin, South Africa

Tatenda Dzurume [a,*], Timothy Dube [a], Cletah Shoko [b]

[a] *Department of Earth Sciences, The University of the Western Cape, Private Bag X17, Bellville, 7535, South Africa*

[b] *Division of Geography, School of Geography, Archaeology, and Environmental Studies, University of Witwatersrand, Private Bag 3, 2050, Johannesburg, South Africa*

ARTICLE INFO

Keywords:
Chlorophyll-*a*
Remote sensing
Southern African Transfrontier River Basin
Water quality monitoring
Water resources
Protected wetland

ABSTRACT

Wetlands in semi-arid regions are highly productive and biologically diverse ecosystems that contribute significantly to livelihood and economic development and play a substantial role in sustaining rural livelihoods. These ecosystems are not only rich in biodiversity, but also predominantly valuable in terms of the services they provide to people, including water security, hydrological regulation, and other services. Chlorophyll-*a* concentrations and associated dynamics in two tropical wetland systems were estimated in the Makuleke and Nylsvlei wetlands. The Makuleke and Nylsvlei wetlands are in the Limpopo Transboundary River Basin, South Africa. Moderate-resolution Landsat 8 images for September 2018 and June 2019 and in situ field measurements were used to estimate and map chlorophyll-*a* concentration from the two wetlands. Landsat-derived chlorophyll-*a* concentrations were validated using field-derived chlorophyll-*a* measurements. Validation was implemented to assess the consistency of the remotely sensed chlorophyll-*a* estimates. The relationship between field-measured chlorophyll estimates and Landsat-derived chlorophyll estimates was determined using the coefficient of determination (r-square: R^2) and the root mean square error (RMSE). The results showed that the Makuleke wetland had low estimates of Chl-*a* during September 2018. The variation of Chl-*a* concentration in Makuleke ranged from 0 to 1.15 μg/L, whereas for Nylsvlei the wetland range varied between 0 and 1.42 μg/L, for the period under study. The spatial characterization of Chl-*a* concentration varied significantly between the two wetlands, with much of it concentrated along the wetland shorelines. The finding of this study underscores the relevance of remotely detected data in the evaluation and routine monitoring of wetland water quality, a previously challenging task within situ measurements.

1. Introduction

Wetland is an area with water table, near or above land surface, either seasonally or permanently throughout the year. Wetlands exist globally in every country (except Antarctica) and in all different types of climates. According to different definitions and estimates, they account for only about 5–8 per cent of the world's land area, but they make up 20–30 per cent of the world's carbon reserve (2500 Pg) (Salimi et al., 2021). The wetlands of South Africa cover about 2.9 million hectares, accounting for about 2.4 per cent of the country's land area. They are recognised as highly valuable natural resources that sustain the livelihoods of local communities by providing a wide-ranging ecosystem goods and services that include, wild fruits, vegetables, rice, and water purification (Dlamini et al., 2021).

Wetlands in semi-arid regions are highly productive and biologically diverse ecosystems that contribute significantly to livelihood and economic development and play a substantial role in sustaining rural livelihoods (Jogo and Hassan 2010; Rebelo et al., 2010). These ecosystems are not only rich in biodiversity but are also predominantly valuable in terms of the services they provide to people, including water security, hydrological regulation, and other services (Dixon et al., 2016). However, these systems are currently decreasing and degrading at an alarming rate. Agriculture is considered the main cause of wetland loss worldwide. It has been estimated that South Africa has already lost between 35 to 50% of its wetlands (Swanepoel and Barnard, 2007). In Craigieburn, Mpumalanga, about 70% of the communities depend on wetlands as the main source of food and income (Scholes and Scholes, 2020). In addition, the study done by Nyamadzawo et al. (2015) stated that many people in Malawi, Zambia, and Zimbabwe use dambos which are seasonal wetlands to provide enough food for local consumption and

* Corresponding author.
E-mail address: 3459290@myuwc.ac.za (T. Dzurume).

https://doi.org/10.1016/j.pce.2022.103193
Received 23 March 2021; Received in revised form 6 June 2022; Accepted 23 June 2022
Available online 28 June 2022
1474-7065/

business purposes and this shows the importance of wetlands. Therefore, the future of these wetlands is dependent on effective and routine assessment and monitoring initiatives that can inform policy and decision-making to promote sustainable management.

Most of the population in sub-Saharan select wetlands in preference to other areas for their agricultural and fishery activities because of their higher productivity and as a result more than half of the wetlands are destroyed through commercial, agricultural, and mining practices as well as urban development (Greenfield et al., 2007; Swanepoel and Barnard 2007; Mitchell, 2013). Southern Africa is rich in mineral resources and some of these minerals occur in areas where there is little water and these activities tend to pollute most of the water resources, including wetlands (Mitchell, 2013). Other threats to African wetlands include changes in wetland water quality due to the effects of industrial effluent and agricultural pesticides, siltation of highland catchment areas, and introduction of alien species of flora and fauna leading to colonization by single species and loss of endemic species diversity (Kabii, 2017). Water quality continues to decrease due to increased population growth and economic development, especially in developing countries. Degradation of water quality poses a threat to human and aquatic life, which raises concerns for the future of water resources (Dube et al., 2015; Masocha et al., 2017). There is, therefore, a need to monitor water quality, although, several factors in Sub-Saharan Africa make it difficult to assess water quality due to; limited technical expertise, limited financial resources, and accessibility and availability of appropriate remote sensing datasets required for accurate water quality monitoring (Dlamini et al., 2016). The other challenge that makes it difficult to monitor water quality in Southern Africa is that the exact number of wetlands is unknown due to the lack of comprehensive national wetland inventories characterizing and classifying wetlands in the systematic wetland (Jogo and Hassan, 2010).

Chlorophyll-*a* (Chl-*a*) is a photosynthetic pigment that is found in all green floral components, including algae (Patra et al., 2017; Amanollahi et al., 2017), and is a critical indicator of wetland health. Chl-*a* has been used as an indicator to identify the biomass of the primary conductivity in coastal areas, estuaries, oceanic waters, and lakes. It has also been widely used as an indicator of water quality because it is possible to estimate algal biomass, which can affect changes in aquatic environments (Baek et al., 2019; Yin et al., 2016). A considerable concentration of phytoplankton and algae is important for the biological productivity and health of a water system. However, excessive concentration of chlorophyll is not desirable because that will cause an increase in the eutrophic condition of a water body and this will result in an increment of phytoplankton in standing crops (Patra et al., 2017). Eutrophication is defined as an aquatic ecosystem's response to nutrient loading, the ability to identify important factors and predict subsequent algal blooms with the use of Chl-*a* is essential regarding water resources management (Bbalali et al., 2013). High levels of Chl-*a* concentrations generally indicate a change in the trophic status of water bodies, and it is usually related to the reduction in water quality and low biodiversity, which severely undermine ecosystem services and functions. To restore these services and functions, it is important to have an understanding of the dynamics of Chl-*a* concentrations (Dalu et al., 2015). High concentrations of chlorophyll may also deteriorate water quality by external and internal nutrient loading, which in most cases leads to the disappearance of benthic fauna and greatly affects aquatic organisms (Patra et al., 2016).

Therefore, different approaches have been developed to estimate and map Chl-*a* concentrations in water bodies. The methods to measure chlorophyll-*a* can be divided into direct and indirect methods (Baek et al., 2019). Direct methods (such as traditional methods) are based on the use of in situ measurements, while indirect methods (such as remote sensing) provide chlorophyll-*a* estimates through the optical water characteristics (Baek et al., 2019). Traditional methods used to assess chlorophyll-*a* depend on in-situ measurements or laboratory analysis of the samples and although this might provide accurate measurements, it is time-consuming and laborious (Abdelmalik, 2018). Field data may be compromised due to inadequate quality control and quality assurance protocols during and after field data collection, especially in cases where field samples have to be stored for a certain period before they can be analysed (Dube et al., 2015). Traditional methods are limited in addressing factors degrading water quality at temporal and spatial scales. In addition, data utility may be compromised due to insufficient quality control and quality assurance protocols such as extended holding time before analysis and the use of non-standardized methods, and the data are often vulnerable to recording and geo-referencing errors during transcription (Dube et al., 2015) On the other hand, remote sensing in assessing chlorophyll-*a* provides information on the physical and chemical properties at temporal and physical scales (Yin et al., 2016).

Remote sensing offers relatively cheap, repetitive, and quantitative methods to monitor water quality, and remote datasets such as Landsat, MODIS, and Sentinel-2 provide both spatial and temporal datasets for water quality monitoring. The use of remotely sensed data to assess water quality data, dates to the early 1920s in different parts of the world (Wang et al., 2004), with Landsat's Thematic Mapper (TM), which is the sensor most widely used since then to monitor inland waters, which uses visible and near-infrared spectral bands. Sensor spectral characteristics and its 30 m pixel resolution have been used to determine the relationship between the reflectance of water bodies and their biophysical parameters, such as Chl-*a* concentration (phytoplankton) and suspended mineral matter in water bodies (Dube et al., 2015). Then recently, the 30 m resolution Landsat 8 Operational Land Imager (OLI) combined with high global data availability, presents a unique platform that provides the first and most up-to-date global inventory of the world's lakes and water quality information retrieval at high spatial resolution and positional accuracy using recent Landsat algorithms (Patra et al., 2016). In the last three decades, remote sensing has played an increasing role in water quality studies, due to its technological advances including instrument/sensor and algorithm/image processing improvements (Dube et al., 2015). Remote sensing has the potential to present synoptic estimates of Chl-*a* concentration in aquatic ecosystems as it provides rapid temporal and synoptic information on the state of the water body, with no interpretive problems associated with under-sampling that are usually experienced through traditional methods (Dalu et al., 2015). Satellite-based remote sensing is increasingly playing a fundamental role in providing valuable information about chlorophyll in water bodies dominated by cyanobacteria and algal blooms around the world (Malahlela et al., 2018). Remote sensing offers the opportunity to drive global variables to evaluate and monitor biodiversity globally and helps to fill the space and time gaps that remain from in situ observations. (Ali et al., 2020).

The purpose of the study was to evaluate and map the changes in chlorophyll-*a* concentration in Makuleke and Nylsvlei wetlands during 2018–2019. Considering that these wetlands are in nature reserves, if they are affected by excessive amounts of chlorophyll, this can greatly affect wetland productivity and their recreational use. This will result in the degrading of the ecosystem value of these wetlands. Therefore, monitoring of Chl-*a* in both unprotected and protected wetlands is of importance because the protection of water resources would satisfy the water demand in different sectors, and aid in assessing water quality in the unmonitored watershed. As field monitoring is expensive and time-consuming, the acquired knowledge would provide guidelines for the management of these water resources.

2. Material and methods

2.1. Description of the study area

The Limpopo Transboundary River Basin (LTRB) is one of the largest catchment areas in Southern Africa and the basin has a mean altitude of 840 m, covering approximately 412 000 km^2 (see Fig. 1(a)) (Sawunyama et al., 2006; Mosase et al., 2019). LTRB is in the eastern part of

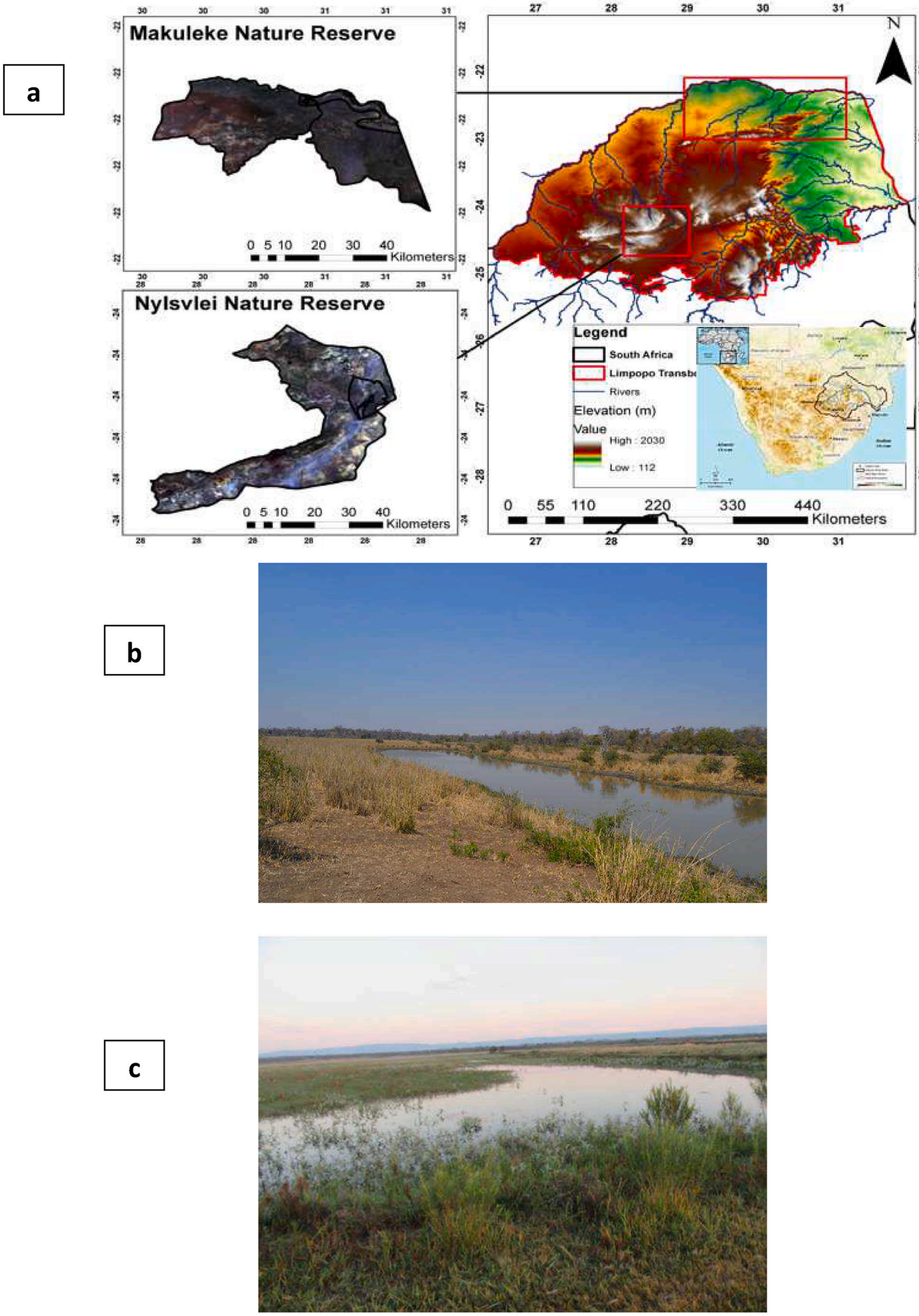

Fig. 1. (a) Locations of the Makuleke and Nylsvlei wetlands within Limpopo; (b) Makuleke and (c) Nylsvlei Nature Reserve wetlands.

Southern Africa approximately between 20° S 26° S and 25° E 35° E at 250 to 2300 m above mean sea level. The basin is shared between four countries, that is, Zimbabwe, South Africa, Mozambique, and Botswana (Gebre and Getahun, 2016), and the basin has 27 major watersheds (Mosase and Ahiablame, 2018). Limpopo Province (South Africa) has experienced a growth in its population from 5 million in 2002 to 5.8 million in 2016 (StatsSA, 2018). The southern and western parts of the catchment are mainly underlined by sedimentary rocks such as sandstone conglomerate, while metamorphic and igneous rocks such as basalt are found in the northern and eastern parts of the LTRB.

The two wetlands understudy, Makuleke and Nylsvlei Nature Reserve wetlands are both listed under Ramsar Convention (see Fig. 1b and c). The Makuleke wetland is in the northern part of LTRB (22°23′S 031°11′E), within Kruger National Park on the floodplains of the Limpopo and Luvhuvhu rivers and bordered by Zimbabwe and Mozambique to the north and east, respectively (Malherbe, 2018; Reid, 2001). The Makuleke wetland covers approximately 240 km^2 and the important landscapes of the nature reserves are riparian forests, grasslands, and pans on floodplains. Floodplains are of great importance in this ecosystem, as they have water even during the dry season and therefore act as a refuge point for wildlife and provide water for birds during both winter and summer months. Nylsvlei wetland is in the southern part of the LTRB (24°39′S 028°42′E). The Nylsvlei wetland covers approximately 40 km^2, and the main features of the Nylsvlei nature reserve include riverine floodplains, flooded river basins, and seasonally flooded grassland, with the dominant wetland type being a seasonal river and associated with a grassland floodplain (Havenga et al., 2007). The wetland has the endangered roan antelope *Hippotragus equis*, and the area serves as a breeding ground for eight South African, red-listed water birds (African and Conservation, 1998; McCarthy et al., 2011).

2.2. Remote sensing data acquisition and pre-processing

Four medium spatial resolution (30 m) multispectral Landsat 8 OLI images were acquired for the two nature reserves (Makuleke and Nylsvlei) between 2018 and 2019 and used to derive chlorophyll-*a* estimates. The Landsat 8 OLI exhibits higher radiometric resolution wavelength coverage compared to Landsat 7 Enhanced Thematic Mapper Plus (ETM +) bands; hence the use of Landsat 8 images. These images were downloaded free of charge from the National Aeronautics and Space Administration (NASA) and United States Geological Earth Explore (USGS) (https://earthexplorer.usgs.gov/). All image data from Landsat 8 OLI were in GeoTIFF format provided by the US Geological Survey Earth Explorer. Table 1 has the specifics of the images that were used. The selection of Landsat satellite images was influenced by the quality of the images, so only images with <10% cloud coverage were selected because cloud cover could compromise the accuracy of the classified images and by the month in which field measurements were taken. The Landsat 8 bands used in this study are available every 16 days with a spatial resolution of 30 m. Satellite image pre-processing before any detection of change is greatly needed and has a primary unique objective of establishing a more direct affiliation between the acquired data and biophysical phenomena (Butt et al., 2015). Atmospheric correction is an important step in any satellite image that observes the surface of the Earth. Therefore, to obtain accurate and precise quantitative data using remote sensing, it is necessary to perform atmospheric correction (Abdelmalik, 2018). The images were reprojected and atmospherically corrected using the semi-automatic classification tool which implements dark object subtraction (DOS1) (the DOS1 atmospheric correction box was checked before the atmospheric correction was run) in the QGIS software.

Table 1
Satellite image specifications.

Catchment	Sensor ID	Path/row	Date
Makuleke	LC08_L1TP_169076	169_076	09–2018
	LC08_L1TP_169076	169_076	06–2019
Nylsvlei	LC08_LITP_170077	170_077	09–2018
	LC08_L1TP_170077	**170_077**	**06–2019**

2.3. In-situ measurements of Chlorophyll-a

Field data measurements were collected in September 2018 and June 2019 from Makuleke and Nylsvlei wetlands, respectively. June was considered the wet season and September the dry season. The mean average of three samples was taken as the value of each point and these samples were collected at the same location during the two seasons (dry and wet). Water samples were collected along the water column during the day at each site and stored on ice for processing in the laboratory. The water samples were used for chlorophyll-*a* extraction in 90% acetone using the spectroscopic method. This is also the same method that was used by Aminot and Rey (2000) and recently by Dalu et al. (2013) to monitor chlorophyll-*a* concentration. The acetone method involves measuring chlorophyll concentrations by extracting chlorophyll dye from the filter paper using acetone. The Chl-*a* concentrations were then calculated by measuring the absorbance of the dye extract at 663, 645, 630, and 750 nm. The actual amount of chlorophyll was measured by the subtraction of the absorbance values at 750 nm from the absorbance values of the sample at 663, 645, and 630 nm. This data set was used for validation and for producing the maps.

2.4. Mapping of wetlands

Multi-Landsat images were classified to derive key land cover types such as up-built areas, bare lands, vegetation, and other water bodies. The normalized difference in water index (NDWI) and normalized difference in vegetation index (NDVI) were also calculated to estimate Chl-*a*. The NDWI provides critical water information and effectively extracts water body information from the land surface features. NDWI is very useful for revealing water-related characteristics of wetlands (Orimoloye et al., 2020). Therefore, this index was used to extract and map wetlands before extracting chlorophyll concentrations in both wetlands. The NDWI index indicates wetness and is used as a wetland inundated area proxy. Where a wetland is covered by hydric soils or is dry, the NDWI values are expected to be low. On the other hand, NDWI values are expected to increase with increasing moisture presence. NDWI was established by McFeeters (1996) (Equation (1)). The NDWI values range from −1 to +1 where positive values predict water and negative values predict non-water.

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

Where NIR is the reflectance in the near-infrared band; Green is the reflectance in the green band.

2.5. Chlorophyll-a estimation from landsat data

This study utilized visible bands (blue, green, and red) and near-infrared (NIR) bands to determine Chl-*a* concentration. The study done by Amanollahi et al. (2017) showed that band 4 with a wavelength between 663 nm and 668nm presents the best results in estimating Chlorophyll-*a*. Normalized Difference Vegetation Index (NDVI) and Chl-*a* have a strong correlation hence both indices are commonly used to measure plant primary productivity and biomass, especially in water bodies such as wetlands (Kulawardhana et al., 2007). As a result of the high NIR reflectance of chlorophyll, the NDVI index was used. NDVI as a commonly used vegetation index can effectively reflect vegetation information (Ma et al., 2018) and can be used as a numerical indicator of biomass and therefore can be used as a proxy for estimating Chl-*a* concentrations from remotely sensed data (Dube, 2012). NDVI is considered one of the most accurate indices in mapping/estimating Chl-*a* (Mwita, 2016). The NDVI was computed using the red and near-infrared bands of the recently launched Landsat 8 multispectral imagery acquired over Makuleke and Nylsvlei wetlands using atmospherically corrected images of Landsat 8. NDVI was calculated following Tucker (1979) as follows:

$$NDVI \quad = \frac{NIR - \mathrm{Red}}{NIR + \mathrm{Red}} \tag{2}$$

Where NIR is the reflectance in the near-infrared region of the electromagnetic spectrum (band 5 of Landsat 8), while red is the reflectance in the red region of the electromagnetic spectrum (band 4 of Landsat 8). NDVI is a dimensionless index with values ranging from −1 to +1. In tropical environments, previous research has shown that NDVI values below 0 indicate water, those above 0 but less than 0.1 are associated with bare surfaces, while those in the range of 0.5 to 1 indicate dense green vegetation (Tucker,1979). However, when wetlands have natural vegetation, the NDVI values will differ depending on the density and vigor of each wetland. Chl-*a* concentration was then derived from the green chlorophyll index, which is measured in μg/L (CI_{green}) (Gitelson et al., 2002)

$$CI_{green} \quad = \frac{NIR}{green} - 1 \tag{3}$$

Where NIR is the reflectance in the near-infrared region of the electromagnetic spectrum (band 5 of Landsat 8), while Green is the reflectance in the green region of the electromagnetic spectrum (band 3 of Landsat 8).

2.6. Accuracy assessment

Landsat-derived chlorophyll-*a* concentrations were validated using field-derived Chl-*a* measurements that were taken during sampling. Five sampling points were used to validate the remotely sensed Chl-*a* estimates. These samples taken in the field were plotted on classified imagery with remotely detected estimates using their GPS coordinates. Validation was implemented to assess the reliability of the remotely sensed Chl-*a* estimates. To achieve this objective, the Root Mean Square (RMSE) was used to assess the predictive error of the model between what is measured in the field and what is predicted using the Landsat imagery. The RMSE is the measure of the average magnitude of the error. Its values range from 0 to infinity. Low RMSE values indicate accurate model estimation and vice versa (see equation (4)) (Dalu et al., 2015). Fig. 2 shows a summary of the methods.

$$RMSE \quad = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{yi})^2} \tag{4}$$

Where, where *yi* is the measured chlorophyll-a concentrations, yi ̂ is Landsat data-derived chlorophyll-a estimates, and n is the number of observations.

3. Results

3.1. Field measurements

In situ Chl-*a* concentrations of Nylsvlei and Makuleke varied significantly, ranging from 0 μg/L to 1.42 μg/L. The highest concentration of Chl-*a* was observed in June 2019 in the Nylsvlei wetland (1.42 μg/L).

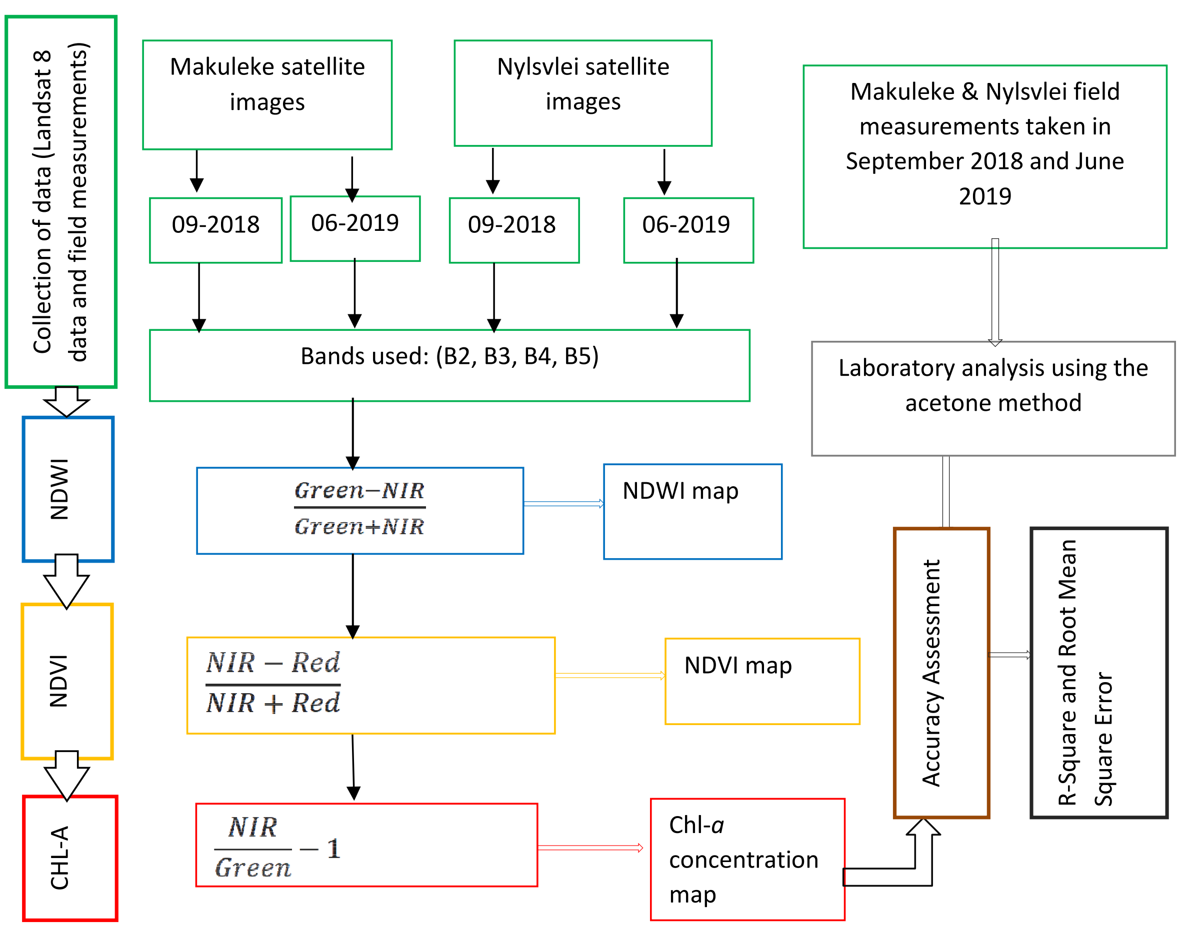

Fig. 2. Summary of the methods used.

Chl-*a* concentrations ranged between 0.27 μg/L and 1.39 μg/L during September 2018 with a mean value of 0.48 μg/L. Makuleke wetland in June 2019, Chl-*a* had a mean of 0.58 μg/L and a standard deviation of 0.38 μg/L. In September 2018, the Chl-*a* concentration ranged between 0.07 μg/L to 0.64 μg/L with a mean value of 0.35 μg/L. During the month of June 2019, Chl-*a* ranged between 0 and 1.42 μg/L (mean = 0.48 μg/L, standard deviation = 0.49 μg/L) for Nylsvlei wetland (see Table 2). Based on the results, it can be concluded that chlorophyll-*a* (Chl-*a*) levels were higher during June and lower in September.

3.2. Chl-a concentration predicted using remote sensing data

The variation in Chl-*a* concentration during the study period is shown in Fig. 3(a and b) for Makuleke and Fig. 3(c and d) for Nylsvlei. The Chl-*a* concentration was mapped using the Cl_{green} index. Chl-*a* concentrations in Makuleke ranged from 0 to 1.15 μg/L and in the Nylsvlei wetland Chl-a ranged from 0 to 1.42 μg/L for the study period. The results showed that most of the Chl-*a* concentrations are found mainly along the edges of the wetlands.

3.3. Comparison of field measurements and remotely detected data

Chlorophyll-*a* concentration results for Makuleke and Nylsvlei wetlands in terms of the coefficient of determination (R^2) and the root mean square error (RMSE) are shown in Fig. 4. The results indicate that Landsat at some points accurately estimated chlorophyll-*a* concentration and underestimated in some areas when compared to the field measurements. Landsat 8 predicted Chl-*a* vs. observed Chl-*a* concentrations produced an R^2 value of 0.95 and a root mean error of 0.04 for September 2018 and for June 2019 the R^2 value of 0.97 and a root mean error of 0.16 μg/L for Makuleke (see Fig. 4 a and b). While for Nylsvlei the R^2 value of 0.95 and 0.06 μg/L RMSE for September 2018 and for June 2019, the R^2 value of 0.92 and 0.26 μg/L RMSE (Fig. 4(c and d)).

4. Discussion

This present study aimed to investigate Chl-*a* concentrations in Nylsvlei and Makuleke Nature Reserve wetlands in the Limpopo Transfrontier River Basin, South Africa. Chl-*a* concentrations were used as an indicator to assess these two wetlands' health. This study demonstrates the importance of using satellite data in monitoring chlorophyll-*a* variations in wetlands, especially in remote areas.

Chl-*a* mainly reflects green and absorbs most energy from wavelengths of violet-blue and orange-red light, which causes chlorophyll to appear green in a water body (Gholizadeh et al., 2016). An increase in Chl-*a* amount may lead to a decrease in light permeability in water and thus a decrease in oxygen produced by photosynthesis (Gönülal and Aslan 2019). From Landsat 8 data acquired for both wetlands, high concentrations of Chl-*a* were estimated to be in the edge part of the wetlands compared to the rest of the wetland. These spatial chlorophyll changes may be a response to seasonal variability. Temperature variations cause a situation in which the growth rates of freshwater eukaryotic phytoplankton generally stabilize, while the growth rates of many cyanobacteria increase, thereby providing a competitive advantage (Paerl and Huisman, 2009). Therefore, as a result, water quality in many wetlands has declined progressively over the past several decades because of the increasing usage of recycled water in wetlands and the inflow of nutrients from agricultural and urban areas (Guo et al., 2017).

Table 2
Chl-*a* summary statistics for Makuleke and Nylsvlei wetlands based on field measurements (September 2018 and June 2019 period).

Parameter	Makuleke		Nylsvlei	
	September 2018	June 2019	September 2018	June 2019
Mean	0.48	0.58	0.35	0.48
Median	0.39	0.46	0.4	0.3
Mode	n/a	n/a	0.4	0.16
Standard Dev.	0.21	0.38	0.19	0.49
Range	0.58	1.12	0.52	1.54
Minimum	0.27	0	0.07	0
Maximum	0.85	1.39	0.64	1.42

Chl-*a* concentrations were considerably higher in June 2019 than in September 2018 for both the Nylsvlei and Makuleke wetlands. Some of the possible reasons why this was the case could be, as shown by Gönülal and Aslan (2019), high concentrations of nitrogen and phosphorus, which are caused by nutrients in aquatic ecosystems. Even though these elements are necessary for the biochemical cycle, are usually incorporated into the water by anthropogenic activities and their excessive amounts lead to eutrophication, which causes serious environmental problems in the aquatic ecosystem. An increase in Chl-*a* concentration in most cases indicates a change in the trophic status of a water body and it is usually associated with a decrease in water quality and low biodiversity which adversely destabilizes the ecosystem services and functions (Dalu et al., 2015). An increase in Chl-*a* concentration may lead to a decrease in light permeability in water and thus a decrease in oxygen produced by photosynthesis, and this usually prevents the bacteria that decompose organic matter in the sediment and restoring the ecosystem (Gönülal and Aslan 2019).

The study by Dalu et al. (2015) showed that low chlorophyll *a* concentrations could most likely be attributed to dilution due to freshwater inflow and increased sediment loads, which would have limited primary production rates. The low Chl-*a* concentration could also be due to a combination of increased water depth and sediment re-suspension taking place in the wetlands or could be caused by dilution due to freshwater inflow and increased sediment loads which would have limited primary production rates. Increased water temperature and low water level may affect dissolved oxygen values, while an increase in chlorophyll-a amounts may lead to a decrease in light permeability in water and thus a decrease in oxygen produced by photosynthesis (Gönülal and Aslan 2019). This can be the case for these wetlands considering where these wetlands are located. The other factor that might have contributed to the low concentrations of Chl-*a* predicted in both study areas is that although estimating chlorophyll through remote sensing techniques is possible, the use of Landsat 8 may not permit discrimination of chlorophyll in waters with high suspended sediments due to dominance of the spectral signature of suspended sediments (Ritchie et al., 2003). The study by Nilsaz et al. (2010) showed that high levels of turbidity affect the predicting of Chl-*a*, and this is most evident during the rainy season compared to the dry season. High water suspended solid affects light penetration in the water resulting in low primary production (Ghorbani, 2016). This might have contributed to the low levels of chlorophyll-*a* predicted in this study.

The concentration changes can be attributed to several factors, especially during planting season in the catchment area, where nutrients are washed into the water body with the first rainfall (Ndungu et al., 2013). At the same time, the rainfall period leads to clearer water, thereby promoting light penetration into the water column. These changes are probably attributable to ever-increasing multiple stressors, such as increased agricultural activities, urbanization, and climate change. Other studies have stipulated that the trophic state is influenced by forcing factors such as eutrophication and sediment load. The effects of forcing factors also can be modified by other accompanying factors such as season, agricultural activities in the catchments, algal grazing, and mixing depth, which, in turn, can play a role in the prevailing water transparency status (Ndungu et al., 2013). Another factor that can affect Chl-*a* concentrations in these wetlands is that wetland species appear to vary greatly in chlorophyll and biomass reflectance as a function of plant species and hydrologic regime. The spectral behaviour of wetland vegetation is also influenced by the water content, which determines the absorption of the mid-infrared region, where red reflectance increases with leaf water stress could results in reduction in chlorophyll

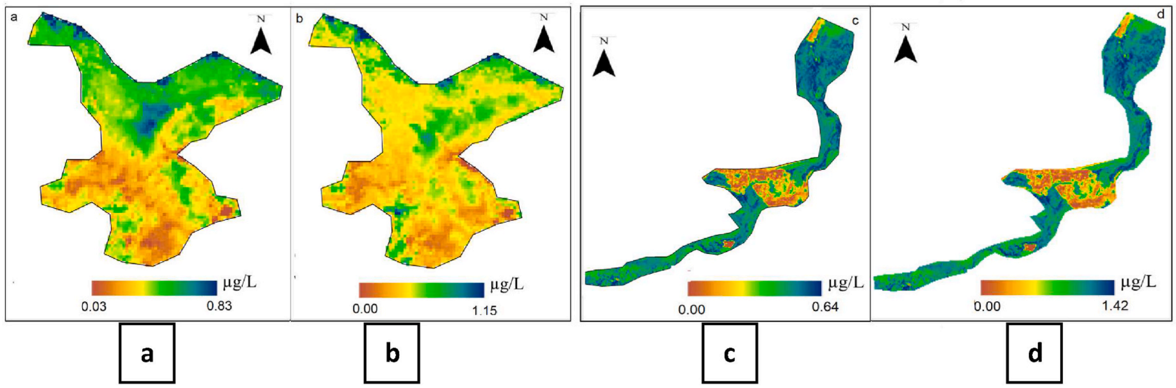

Fig. 3. (a–b): Depicts Chl-*a* concentrations over the Makuleke wetland during (a) September 2018 and (b) June 2019, (c–d): Landsat derived spatial distribution Chl-*a* concentrations over the Nylsvlei wetland during (c) September 2018 and (d) June 2019.

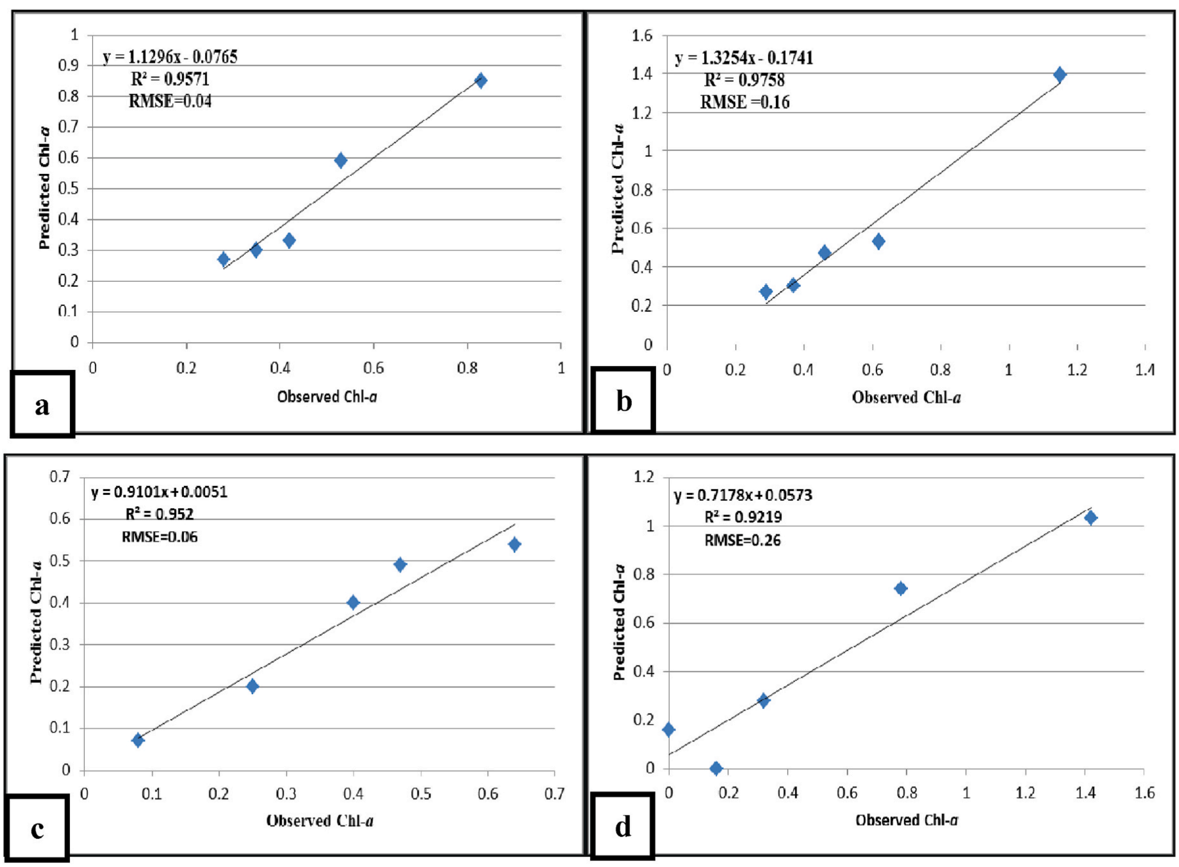

Fig. 4. (a–d): Relationship between observed (field measurements) and predicted (Chl-*a*) values (a) September 2018, (b) June 2019 for Makuleke wetland, (c) September 2018, and (d) June 2019 for Nylsvlei wetland.

concentration (Adam et al., 2010). Therefore the finding of this study underscores the relevance of remotely detected data in the evaluation and routine monitoring of wetland water quality.

5. Conclusions

The study aimed to assess and map chlorophyll-*a* concentration changes in Makuleke and Nylsvlei wetlands during the 2018–2019 period. Chlorophyll-*a* is an indicator of the abundance of phytoplankton, which makes an important contribution to the overall primary productivity of water bodies, such as wetlands. Therefore, the use of remote sensing techniques to predict and map the concentration is important in the monitoring and assessment of water quality in wetlands, especially because of the ability of remote sensing techniques to measure chlorophyll concentrations spatially and temporally. The results demonstrate that Landsat 8 OLI data could provide a useful tool for investigating the spatio-temporal variability of Chl-*a* in wetlands, particularly in remote areas that are not easily accessible.

Author statement

Attached is the manuscript titled "**Remote sensed data in estimating chlorophyll-*a* concentration in wetlands located in the Limpopo Transboundary River Basin, South Africa.**" The manuscript focuses on Chlorophyll-*a* concentrations and associated dynamics in two tropical wetland systems were estimated. Makuleke and Nylsvlei wetlands are located in the Limpopo Transboundary River Basin, South Africa. September 2018 and June 2019 Moderate resolution Landsat 8 images and in-situ field measurements were used to estimate and map chlorophyll-*a* concentrations from the two wetlands. Landsat-derived chlorophyll-*a* concentrations were validated using field-derived chlorophyll-*a* measurements. Validation was implemented to assess the consistency of the remotely sensed chlorophyll *a* estimates. The relationship between field measured and Landsat data-derived chlorophyll estimates were determined using the coefficient of variation (r-square: R^2) and the Root Mean Square Error (RMSE). The results show that Makuleke wetland had low estimates during the month of September 2018 and June 2019. The variation of chl-*a* concentration in Makuleke ranged from -0 to 1.15 μg/L whereas for Nylsvlei wetland the ranges varied between -0 and 1.42 μg/L, for the period understudy. Spatial characterization of Chl-*a* concentrations significantly varied across the two wetlands with much of it concentrated along wetland shorelines. The finding of this study underscores the relevance of remotely sensed data in assessing and routine monitoring wetland water quality-previously challenge task with in-situ measurements.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank the anonymous reviewers for their valuable input in this article and the Global Monitoring for Environment and Security (GMES)-Africa through SASCAL and WeMAST project for funding this entire project. The authors would also like to thank, Mr Siyamthanda Gxokwe, Mr Eugene Sagwati Maswanganye and Dr Tatenda Dalu for their assistance in the field and data collection.

References

Abdelmalik, K.W., 2018. Role of statistical remote sensing for inland water quality parameters prediction. Egypt. J. Remote Sens. Space Sci. 21 (2), 193–200. https://doi.org/10.1016/j.ejrs.2016.12.002.

Adam, Elhadi, Mutanga, Onisimo, Rugege, Denis, 2010. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. Wetl. Ecol. Manag. 18 (3), 281–296. https://doi.org/10.1007/s11273-009-9169-z.

African, S., Conservation, W., 1998. *Nylsvlei nature reserve*. List of wetlands of international importance: convention on wetlands of international importance especially as waterfowl habitat. South Afr. Wetl. Conserv. Programme. Document No 24121131313117.

Ali, A., Darvishzadeh, R., Skidmore, A., Heurich, M., Paganini, M., Heiden, U., Mücher, S., 2020. Remote sensing evaluating prediction models for mapping canopy chlorophyll. Content Across Biomes 12, 1788. https://doi.org/10.3390/rs12111788, 8.

Amanollahi, Jamil, Kaboodvandpour, Shahram, Majidi, Hiva, 2017. Evaluating the accuracy of ANN and LR models to estimate the water quality in zarivar international wetland, Iran. Nat. Hazards 85 (3), 1511–1527. https://doi.org/10.1007/s11069-016-2641-1.

Aminot, A., Rey, F., 2000. Standard procedure for the determination of chlorophyll a by spectroscopic methods. In: ICES Techniques in Marine Environmental Sciences. Copanhagen, Denmark, pp. 8–11.

Baek, Ji Yeon, Young, Heon Jo, Kim, Wonkook, Seok Lee, Jong, Jung, Dawoon, Kim, Dae Won, Nam, Jungho, 2019. A new algorithm to estimate chlorophyll-a concentrations in turbid yellow sea water using a multispectral sensor in a low-altitude remote sensing system. Rem. Sens. 11 (19) https://doi.org/10.3390/rs11192257.

Bbalali, Saeed, Abbas Hoseini, Seyed, Ghorbani, Rasool, Kordi, Hamideh, 2013. Relationships between nutrients and chlorophyll a concentration in the international alma gol wetland, Iran. J. Aquacult. Res. Dev. 4 (3) https://doi.org/10.4172/2155-9546.1000173.

Butt, Amna, Shabbir, Rabia, Saeed Ahmad, Sheikh, Aziz, Neelam, 2015. Land use change mapping and analysis using remote sensing and GIS: a case study of simly watershed, Islamabad, Pakistan. Egypt. J. Remote Sens. Space Sci. 18 (2), 251–259. https://doi.org/10.1016/j.ejrs.2015.07.003.

Dalu, Tatenda, Nhiwatiwa, Tamuka, Dalu, Tatenda, Clegg, Bruce, 2013. Temporal variation of the plankton communities in a small tropical reservoir (Malilangwe, Zimbabwe). Trans. Roy. Soc. S. Afr. 68 (2), 85–96. https://doi.org/10.1080/0035919X.2013.766280.

Dalu, Tatenda, Dube, Timothy, William Froneman, P., Mwazvita, T., Sachikonye, B., Clegg, Bruce W., Nhiwatiwa, Tamuka, 2015. An assessment of chlorophyll-a concentration spatio-temporal variation using Landsat satellite data, in a small tropical reservoir. Geocarto Int. 30 (10), 1130–1143. https://doi.org/10.1080/10106049.2015.1027292.

Dixon, M.J.R., Loh, J., Davidson, N.C., Beltrame, C., Freeman, R., Walpole, M., 2016. Tracking global change in ecosystem Area: the wetland extent trends index. Biol. Conserv. 193, 27–35. https://doi.org/10.1016/j.biocon.2015.10.023.

Dlamini, S., Nhapi, I., Gumindoga, W., Nhiwatiwa, T., Dube, T., 2016. Assessing the feasibility of integrating remote sensing and in-situ measurements in monitoring water quality status of lake Chivero, Zimbabwe. Phys. Chem. Earth 93, 2–11. https://doi.org/10.1016/j.pce.2016.04.004.

Dlamini, M., Chirima, G., Sibanda, M., Adam, E., Dube, T., 2021. Remote Sensing Characterizing Leaf Nutrients of Wetland Plants and Agricultural Crops with Nonparametric Approach Using Sentinel-2 Imagery Data. https://doi.org/10.3390/rs13214249.

Dube, Timothy, 2012. Primary Productivity of Intertidal Mudflats in the Wadden Sea: A Remote Sensing Method. University of Twente, pp. 1–68. https://www.itc.nl/library/papers_2012/msc/wrem/dube.pdf.

Dube, T., Mutanga, O., Seutloali, K., Adelabu, S., Shoko, C., 2015. Water quality monitoring in sub-Saharan African lakes: a review of remote sensing applications. Afr. J. Aquat. Sci. 40 (1), 1–7. https://doi.org/10.2989/16085914.2015.1014994.

Legesse Gebre, Sintayehu, Sineshaw Getahun, Yitea, 2016. Analysis of climate variability and drought frequency events in Limpopo river basin, South Africa. J. Waste Water Treat. Anal. 7 (3) https://doi.org/10.4172/2157-7587.1000249.

Gholizadeh, Mohammad Haji, Melesse, Assefa M., Reddi, Lakshmi, 2016. A comprehensive review on water quality parameters estimation using remote sensing techniques. Sensors 16 (8). https://doi.org/10.3390/s16081298.

Ghorbani, R., 2016. Evaluation of effects of physico-chemical factors on chlorophyll-a in shadegan international wetland-khouzestan province - Iran. Iran. J. Fish. Sci. 15 (1), 360–368.

Gitelson, A.A., Viña, A., Ciganda, V., Rundquist, D.C., Arkebauer, T.J., 2002. Remote estimation of canopy chlorophyll content in crops. Geophys. Res. Lett. 32, 08-403.

Gönülal, O., Aslan, H., 2019. Determination of some macro element concentrations and chlorophyll-a distribution in a shallow lake wetland (Gökçeada salt lake lagoon, Çanakkale/Turkey). J. Sci. Perspect. 3 (2), 111–118. https://doi.org/10.26900/jsp.3.012.

Greenfield, R., Van Vuren, J., Wepener, V., 2007. Determination of sediment quality in the Nyl River system, Limpopo Province, South Africa. Water SA 33 (5), 693–700. https://doi.org/10.4314/wsa.v33i5.184090.

Guo, Meng, Jing, Li, Sheng, Chunlei, Xu, Jiawei, Wu, Li, 2017. A review of wetland remote sensing. Sensors 17 (4), 1–36. https://doi.org/10.3390/s17040777.

Havenga, C.F.B., Pitman, W.V., Bailey, A.K., 2007. Hydrological and hydraulic modelling of the nyl river floodplain Part 1. Background and hydrological modelling. WaterSA 33 (1), 1–8. https://doi.org/10.4314/wsa.v33i1.47865.

Jogo, Wellington, Hassan, Rashid, 2010. Balancing the use of wetlands for economic well-being and ecological security: the case of the Limpopo wetland in southern Africa. Ecol. Econ. 69 (7), 1569–1579. https://doi.org/10.1016/j.ecolecon.2010.02.021.

Kabii, Tom, 2017. An Overview of African Ethics.” *Themes, Issues And Problems In African Philosophy*, vols. 61–75. https://doi.org/10.1007/978-3-319-40796-8_5.

Kulawardhana, R.W., Thenkabail, Prasad S., Vithanage, J., Biradar, C., Islam, Md A., Gunasinghe, S., Alankara, R., 2007. Evaluation of the wetland mapping methods using Landsat ETM+ and SRTM data. J. Spatial Hydrol. 7 (2), 62–96.

Ma, Fawang, Wang, Qiubing, Zhang, Maoxin, 2018. Dynamic changes of wetland resources based on MODIS and Landsat image data fusion. Eurasip J. Image Video Proces. 2018 (1) https://doi.org/10.1186/s13640-018-0305-7.

Malahlela, Oupa, Oliphant, Thando, Tsoeleng, Lesiba, Mhangara, Paidamwoyo, 2018. Mapping chlorophyll- a concentrations in a cyanobacteria- and algae-impacted vaal dam using. Landsat 8 OLI Data 114 (9), 1–9.

Malherbe, Wynand, 2018. Ramsar wetlands in South Africa : historic and current aquatic research ramsar wetlands in South Africa. South Afr. J. Sci. Technol. 37 (1), 1–13. http://www.satnt.ac.za.

Masocha, Mhosisi, Amon Murwira, Magadza, Christopher H.D., Hirji, Rafik, Dube, Timothy, 2017. Remote sensing of surface water quality in relation to catchment condition in Zimbabwe. Phys. Chem. Earth 100, 13–18. https://doi.org/10.1016/j.pce.2017.02.013.

McCarthy, Terence S., Tooth, Stephen, Jacobs, Zenobia, Rowberry, Matthew D., Thompson, Mark, Brandt, Dion, John Hancox, P., Marren, Philip M., Woodborne, Stephan, Ellery, William N., 2011. The origin and development of the nyl river floodplain wetland, Limpopo province, South Africa: trunk-tributary river interactions in a dryland setting. S. Afr. Geogr. J. 93 (2), 172–190. https://doi.org/10.1080/03736245.2011.619324.

McFeeters, S.K., 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. Int. J. Rem. Sens. 17, 1425–1432.

Mitchell, Stephen Anthony, 2013. The status of wetlands, threats and the predicted effect of global climate change: the situation in sub-saharan Africa. Aquat. Sci. 75 (1), 95–112. https://doi.org/10.1007/s00027-012-0259-2.

Mosase, Esther, Ahiablame, Laurent, 2018. Rainfall and temperature in the Limpopo river basin, southern Africa: means, variations, and trends from 1979 to 2013. Water (Switzerland) 10 (4). https://doi.org/10.3390/w10040364.

Mosase, Esther, Laurent, Ahiablame, Srinivasan, Raghavan, 2019. Spatial and temporal distribution of blue water in the Limpopo river basin, southern Africa: a case study.

Ecohydrol. Hydrobiol. 19 (2), 252–265. https://doi.org/10.1016/j.ecohyd.2018.12.002.
John Mwita, Emiliana, 2016. Monitoring restoration of the eastern usangu wetland by assessment of land use and cover changes. Adv. Rem. Sens. 145–156. https://doi.org/10.4236/ars.2016.52012, 05 (02).
Ndungu, Jane, Augustijn, Denie C.M., Hulscher, Suzanne J.M.H., Kitaka, Nzula, Mathooko, Jude, 2013. Spatio-temporal variations in the trophic status of lake naivasha, Kenya. Lakes Reservoirs Res. Manag. 18 (4), 317–328. https://doi.org/10.1111/lre.12043.
Nilsaz, Khlifeh M., Sabzalizadeh, S., Esmaiili, F., Ansari, H., Eskandari, G., Hashemi, A., Abu Obeid, S., 2010. Monitoring of Shadegan Wetland, 150P. South aquaculture research center of Iran.
Nyamadzawo, G., Wuta, M., Nyamangara, J., Nyamugafata, P., Chirinda, N., 2015. Optimizing dambo (seasonal wetland) cultivation for climate change adaptation and sustainable crop production in the smallholder farming areas of Zimbabwe. Int. J. Agric. Sustain. 13 (1), 23–39. https://doi.org/10.1080/14735903.2013.863450.
Orimoloye, Israel R., Kalumba, Ahmed M., Mazinyo, Sonwabo P., Werner, Nel, 2020. Geospatial analysis of wetland dynamics: wetland depletion and biodiversity conservation of isimangaliso wetland, South Africa. J. King Saud Univ. Sci. 32 (1), 90–96. https://doi.org/10.1016/j.jksus.2018.03.004.
Patra, Pulak Priti, Dubey, Sourabh Kumar, Kumar Trivedi, Raman, Kumar Suhu, Sanjeev, Keshari Rout, Sangram, 2016. Estimation of chlorophyll-a concentration and trophic states for an inland lake from landsat-8 OLI data: a case Nalban lake of east Kalkota wetland, India. Preprints. https://doi.org/10.20944/preprints201608.0149.v1. August: 18.
Patra, Pulak Priti, Dubey, Sourabh Kumar, Kumar Trivedi, Raman, Kumar Sahu, Sanjeev, Keshari Rout, Sangram, 2017. Estimation of chlorophyll-a concentration and trophic states in nalban lake of east Kolkata wetland, India from Landsat 8 OLI data. Spatial Inf. Res. 25 (1), 75–87. https://doi.org/10.1007/s41324-016-0069-z.
Rebelo, L.M., McCartney, M.P., Finlayson, C.M., 2010. Wetlands of sub-saharan Africa: distribution and contribution of agriculture to livelihoods. Wetl. Ecol. Manag. 18 (5), 557–572. https://doi.org/10.1007/s11273-009-9142-x.
Reid, Hannah, 2001. Contractual national parks and the Makuleke community. Hum. Ecol. 29 (2), 135–155. https://doi.org/10.1023/A:1011072213331.
Ritchie, Jerry C., Zimba, Paul V., Everitt, James H., 2003. Remote sensing techniques to assess water quality. Photogramm. Eng. Rem. Sens. 69 (6), 695–704. https://doi.org/10.14358/PERS.69.6.695.
Salimi, S., Almuktar, S.A.A.N., Scholz, M., 2021. Impact of climate change on wetland ecosystems: a critical review of experimental wetlands. J. Environ. Manag. 286, 112160 https://doi.org/10.1016/J.JENVMAN.2021.112160.
Sawunyama, T., Senzanje, A., Mhizha, A., 2006. Estimation of small reservoir storage capacities in Limpopo river basin using geographical information systems (GIS) and remotely sensed surface areas: case of mzingwane catchment. Phys. Chem. Earth 31 (15–16), 935–943. https://doi.org/10.1016/j.pce.2006.08.008.
Scholes, M., Scholes, R., 2020, September 16. A keen eye on facts saved this biodiverse wetland for now: threats to be aware of'. The Conversation. Available at. https://theconversation.com/a-keen-eye-on-facts-saved-this-biodiverse-wetland-for-now-threats-to-be-aware-of-145270.
StatsSA, 2018. Community Survey 2016: Provincial Profile: Limpopo. http://cs2016.statssa.gov.za/wp-content/uploads/2018/07/Limpopo.pdf.
Swanepoel, C.M., Barnard, R.O., 2007. Discussion paper: wetlands in agriculture. Department of water affairs and forestry. *South Africa*. Vol. GW/A/2007/. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:DISCUSSION+PAPER+:+Wetlands+in+Agriculture#7.
Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Rem. Sens. Environ. 8, 127–150.
Wang, Yunpeng, Xia, Hao, Fu, Jiamo, Sheng, Guoying, 2004. Water quality change in reservoirs of shenzhen, China: detection using LANDSAT/TM data. Sci. Total Environ. 328 (1–3), 195–206. https://doi.org/10.1016/j.scitotenv.2004.02.020.
Yin, Changming, He, Binbin, Quan, Xingwen, Liao, Zhanmang, 2016. Chlorophyll content estimation in arid grasslands from landsat-8 OLI data. Int. J. Rem. Sens. 37 (3), 615–632. https://doi.org/10.1080/01431161.2015.1131867.