

Remote sensing-based algorithms for water quality monitoring in Olushandja Dam, north-Central Namibia

Taimi S. Kapalanga, Zvikomborero Hoko, Webster Gumindoga and Loyd Chikwiramakomo

ABSTRACT

Frequent and continuous water quality monitoring of Olushandja Dam in Namibia is needed to inform timely decision making. This study was carried out from November 2014 to June 2015 with Landsat 8 reflectance values and field measured water quality data that were used to develop regression analysis-based retrieval algorithms. Water quality parameters considered included turbidity, total suspended solids (TSS), nitrates, ammonia, total nitrogen (TN), total phosphorus (TP) and total algae counts. Results show that turbidity levels exceeded the recommended limits for raw water for potable water treatment while TN and TP values are within acceptable values. Turbidity, TN, and TP and total algae count showed a medium to strong positive linear relationship between Landsat predicted and measured water quality data while TSS showed a weak linear relationship. The regression coefficients between predicted and measured values were: turbidity ($R^2 = 0.767$); TN ($R^2 = 0.798$); TP ($R^2 = 0.907$); TSS ($R^2 = 0.284$;) and total algae count ($R^2 = 0.851$). Prediction algorithms are generally best fit to derive water quality parameters. Remote sensing is recommended for frequent and continuous monitoring of Olushandja Dam as it has the ability to provide rapid information on the spatio-temporal variability of surface water quality.

Key words | Landsat 8, Olushandja Dam, reflectance values, regression algorithms, remote sensing, retrieval, water quality

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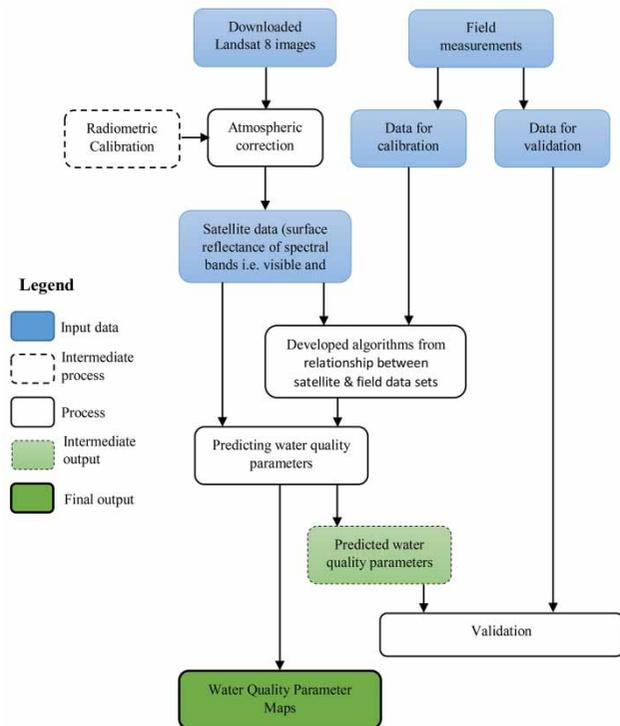
HIGHLIGHTS

- Over past years, frequent and continuous water quality monitoring problematic in Namibia.
- A linear regression can now be used to develop algorithms for retrieving water quality data.
- Good prediction accuracy for turbidity, TN, TP and total algae count.
- More sampling points needed to further improve regression model accuracy.
- Remote sensing provides rapid information on the water quality spatio-temporal variability.

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GRAPHICAL ABSTRACT



INTRODUCTION

Fresh water is a finite resource that is essential for human existence (Maestu 2018; Bhuyar *et al.* 2019a, 2019b; Bhuyar *et al.* 2020). Without freshwater of adequate quantity and quality, sustainable development will not be possible (UN-Water 2011; Mcmillan *et al.* 2017). Effective management of this scarce resource ensures that present generations' needs do not deprive future generations the same privileges of access in both quantity and quality as envisioned in the Sustainable Development Goals (SDGS) (Bain *et al.* 2020). Therefore, Integrated Water Resources Management (IWRM) is an essential approach as it emphasizes on effective management of water resources within the basin.

In the Southern Africa Region, pollution of both surface and ground water is on the increase, particularly from mining, agricultural and industrial activities (SADC 2005). Man-made reservoirs such as dams and lakes are threatened by nutrient enrichment and heavy metals and their water quality is continuously degraded as a result (Oberholster

& Ashton 2008; Nhapi 2009; Lehmann 2010). For example, the water quality in Von Bach and Swakoppoort Dam in the Central Area of Namibia has been reported to be poor due to treated and at times partially treated wastewater from the City of Windhoek and Okahandja town (Lehmann 2010; NamWater 2012).

In the north central regions of Namibia, poor sanitation practices are notably high (IWRMPJVN 2010), with about 67% of the population having no access to improved sanitation facilities (UN 2010). North-central Namibia is more vulnerable to effects of climate change and variability. Combined effects of environmental degradation, social vulnerability to poverty and a changing climate will compromise water and sanitation provision (Angula & Kaundjua 2016). Flash floods are further predicted to impact overall sanitation and human health conditions (Kaundjua *et al.* 2012). Therefore, during high rainfall events, cholera outbreak has been reported due to wash away of water and

wastewater aided by poor and inadequate sanitation facilities in the areas (UN 2011).

Shuuya & Hoko (2014) found that the quality of water in the Calueque – Oshakati canal is deteriorating from upstream to downstream due to human activities along the canal such as agriculture, settlements and mining. All these activities tend to affect the quantity and quality of water leading to an increase in the cost of purifying water for human consumption. The IWRMPJVN (2010) noted that lack of data, continuous monitoring and poor data management exist in the Namibian water sector. Water quality monitoring in many southern African countries including Namibia has been noted to be hindered by lack of data, capacity and resources (SADC 2005). Water quality monitoring in Namibia has been noted to be one of the key issues that requires urgent attention by researchers and water managers.

Few studies that are available for the Kunene River and Cuvelai Basins in the north-central regions of Namibia focus on ad-hoc monitoring. Hambabi (2015) and other studies focused on the quality of water in the canals that bring water into the Olushandja Dam and to the treatment plants (Shuuya & Hoko 2014) and transport water from the dam (SDPIO 2001). These studies mainly employ traditional insitu-based methods of determining water quality. According to the IWRMPJVN (2010), determining water quality using traditional techniques is costly and may be one of the major contributors to poor monitoring framework not only in Namibia but also in many developing countries in the world. Ritchie *et al.* (2003) stated that, traditional methods for assessing and monitoring water quality are expensive and time consuming. In addition, they do not give spatial or temporal view of water quality needed for accurate assessment of water bodies, therefore the need for more robust techniques which have a spatial and a temporal dimension (Kallio 2017).

Thus, this study explored the applicability of remote sensing in combination with insitu-observed measurements to develop algorithms and prediction of selected water quality parameters in Olushandja Dam. Remote sensing based water quality assessment is an economical way to monitor water quality, since it allows routine monitoring of large areas in a short time and on a repetitive basis (Hellweger *et al.* 2004; Somvanshi *et al.* 2012). According to Ritchie

et al. (2003), the use of remote sensing in water quality dated back to 1970s. Namibia is one of the countries with the most number of sunshine days or cloud free sky which make it easy for optical remote sensing application in the visible and infrared regions of the electromagnetic spectrum. Information obtained from this study will help the institutions responsible for management of Olushandja Dam such as NamWater and Namibian community-based water management (CBWM) Kelbert (2016) to carry out continuous monitoring of the quality of water in an economical way for decision making.

However the major constraints would be the lack of reliable retrieval algorithms, cost of satellite data and equipment's for in-situ, on-site and laboratory measurements of water quality parameters (Bauer *et al.* 2007). For the retrieval of water quality parameters from different satellite sensors, a number of methods has been used which range from empirical, semi-empirical to analytical techniques (Schalles *et al.* 1998; Wang & Ma 2001; Dekker *et al.* 2002; Brando & Dekker 2003; Vignolo *et al.* 2006; Chen *et al.* 2007; He *et al.* 2008; Maillard & Pinheiro Santos 2008; Salama *et al.* 2009; Olet 2010; Chawira *et al.* 2013; Kibena *et al.* 2014). The advantage of satellite remote sensing techniques lies in its capacity to allow managers to detect and control the pollutants before they reach alarming levels (Helmer *et al.* 1997). The water quality parameters that has been assessed include chlorophyll-a, suspended matter and turbidity as they are most likely to change the water colour (Schalles *et al.* 1998; Li 2009; Salama *et al.* 2009; Olet 2010; Kibena *et al.* 2014). In Belbok Spruit, South Africa, du Plessis *et al.* (2014) predicted water quality from landcover changes using Partial Least Squares regression analysis. Yang & Jin (2010) predicted NO₃ using spatial regression method for Iowa River in the United States and obtained acceptable R² of 0.8. Most researchers in Sub-Saharan Africa have also applied earth observation techniques in the retrieval of water quality parameters mainly for lakes and dams (Chawira *et al.* 2013; Kibena *et al.* 2014, Dube *et al.* 2015). There is still need to explore in greater depth the application of earth observation techniques for predicting water quality parameters especially in developing countries where land use changes are pertinent (du Plessis *et al.* 2014; Chapra 2015, Hiyama 2017).

A few studies have attempted to monitor and model nutrients (such as total nitrogen, phosphorus, nitrate etc.) and proven the ability of remote sensing for these predictions (Alparslan *et al.* 2007; He *et al.* 2008; Chen & Quan 2012). Most of the nutrient prediction models developed so far are based on statistical regression approaches. Predicting water quality characteristics from remote sensing requires ground-truthing and validation data (Blake *et al.* 2013). Therefore, assessment and monitoring of water quality using the combination of remote sensing and in-situ measurements plays a significant role in providing reasonable and accurate optically constituents of water (Salama *et al.* 2009).

Remote sensing based water quality assessment and monitoring may use the same method of retrieval or predicting water quality parameter, but the available sensor types may differ (Tomppo *et al.* 2002; USGS 2013). These include Moderate Resolution Imaging Spectroradiometer (MODIS), Medium Resolution Imaging Spectrometer (MERIS), SPOT, and Landsat which differ in spatial, temporal, number of spectral bands and pixels. Landsat used in this study, has a fair revisit time (16 days) and better resolution (30 m) than most medium resolution sensors. In addition, Landsat imagery are available free of charge from archive hosted by the USGS Earth Resources Observation and Science (EROS) Centre. The Landsat mission represent the longest continuous satellite record of the earth, beginning in 1972 with Landsat 1 and currently with the operation of Landsat 8 (USGS 2013). The different Landsat satellite mission images have been used in a number of water quality studies (Zuccari *et al.* 1993; Wang *et al.* 2004; Vignolo *et al.* 2006; Weiqi *et al.* 2008; Olet 2010; Somvanshi *et al.* 2012; Waxter 2014; Bonansea *et al.* 2015). The best correlations between remote sensing signal and insitu observed water quality parameters were found mainly in the visible (blue, Green, Red) and near infrared spectral range.

The objectives of this study were: (i) to characterize the status of the quality of water in Olushandja dam through insitu-observed measurements, (ii) develop algorithms for predicting selected water quality parameters through satellite and insitu-observed measurements and (iii) to predict selected water quality parameters from remote sensing as a framework for continuous monitoring of water quality in Olushandja Dam.

STUDY AREA

Olushandja Dam is located in the upper western part of Omusati Region in Olushandja Sub-Basin of the Cuvelai-Etosha Basin in North Central of Namibia (Figure 1). The Namibian part of the Cuvelai Basin covers an area between the Okavango and Kunene Rivers and ends up in the Etosha Pan. The basin covers an area of approximately 250,053 km² from the Namibia-Angola border terminating in the Etosha Pan (Kolberg 2002). The Cuvelai lies within a relatively small depression along the western margins of the vast Kalahari Basin that covers much of south-central Africa. The basin is made up of shallow pans known as 'Iishana', which form a network of shallow ephemeral river system.

The Cuvelai Basin in north-central Namibia comprises a unique system of seasonal wetlands and constitutes some of the areas having the highest human population densities in Namibia (50–100 persons/km²). The region carries about 40% of Namibia's population of about 2.2 million people Niipele *et al.* (2015). The Cuvelai-Etosha Basin and Namibia as a whole is characterized by a semi-arid to arid climate and desert environment (Mendelsohn *et al.* 2000, 2013). The average temperatures vary between 20 °C and greater than 22 °C in most areas. This translate to the potential evaporation that ranges between 2,600 and 3,200 mm per year, much higher than the yearly amount of rainfall (CuveWater 2014). The geomorphology of the Cuvelai Basin is complex. Mendelsohn *et al.* (2016) has provided a comprehensive description of the Cuvelai Basin landscapes and how the characteristics of these landscapes have influenced human settlement patterns.

The Olushandja Dam lies between 1,100 and 1,150 metres above sea level (CuveWater 2014). Olushandja Dam has a surface area of about 29.0 km² and capacity of around 42.331 Mm³ when full (NamWater 2013). The dam is about 20 km long and varies between 200 m and 2,000 m in width (Mendelsohn *et al.* 2000). The dam was built in 1973 during the country's liberation struggle in the old Etaka Channel to act as a balancing reservoir that stores water during excess flows of the Kunene River. In addition, the dam was built to provide a strategic reserve in the event of supplies from Calueque Dam in Angola being interrupted. In 1990 the system was renovated and now raw surface water is transferred from Calueque Dam

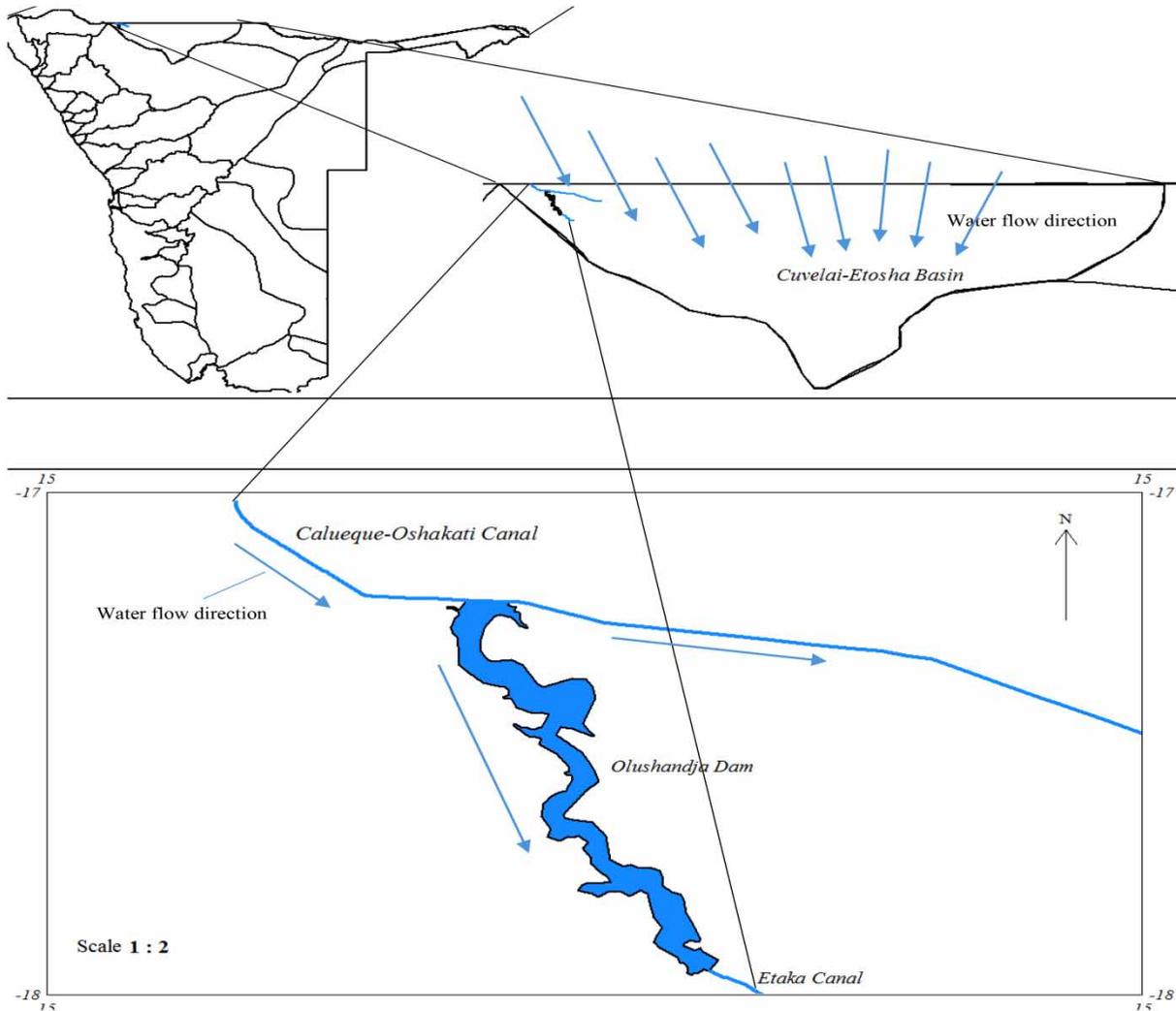


Figure 1 | The study area in relation to Cuvelai-Etoshia Basin.

in Angola through a concrete open canal into the dam and also to four treatment plants in the region. In recent years, the dam is held at 50% capacity and since its construction, more than 100 households have been built in the dam flood plain. (Mendelsohn *et al.* 2000; NamWater 2013).

MATERIALS AND METHODS

Field data collection

Sampling points (Figure 2) in the dam were selected systematically to reflect on the impacts of major tributaries' landcover activities on the dam water quality. Parameters

were also selected taking into account the relationship between pollution sources and different water quality parameters including their potential impacts on human, aquatic life and environmental health. In addition, the selection considers water quality parameters that are known to be successfully retrieved from satellite data. Turbidity, algae and nutrients are known to have been successfully retrieved from satellite data (Zuccari *et al.* 1993; Hellweger *et al.* 2004; Wang *et al.* 2004; He *et al.* 2008; Li 2009; Olet 2010; Irenosen *et al.* 2012; Chawira *et al.* 2013; Waxter 2014; Bonansea *et al.* 2015).

Representative water samples were collected from six systematically selected locations in the Olushandja Dam following the Landsat imagery capturing calendar obtained from USGS (earthexplorer.usgs.gov). At each sampling

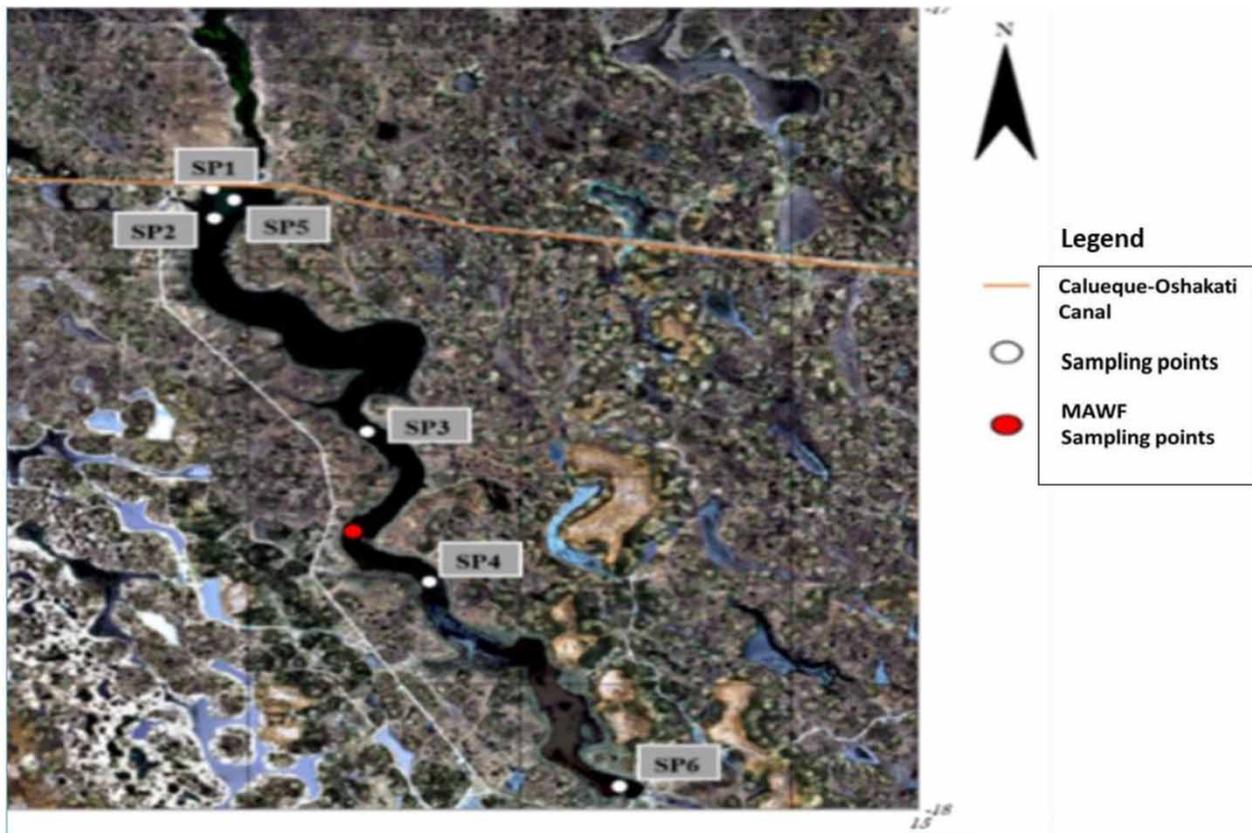


Figure 2 | Sampling points location on a geometrically corrected Landsat 8 OLI image of 2015.

point, grab water samples were taken at about 10 cm depth below the surface using three 500 ml bottles with screw-cap. The sampling campaigns were done twice a month between the January and April 2015 from 08:30 am to 14:00 pm. On the same day, satellite images were taken, the insitu-observed measurements were done because a time difference between insitu-observed measurements and satellite measurements is an important aspect (Hellweger *et al.* 2004). The water samples were collected, preserved, transported and analysed according to the Standard Methods for Water and Wastewater described by (APHA 2012).

Satellite data retrieval

Landsat 8 images of Path 180; Row 072 which covers Olushandja Dam were downloaded from Landsat imagery archive hosted by the USGS Earth Resources Observation and Science (EROS) Centre using the USGS Globalization Visualization Viewer (Glovis) tool. Figure 3 displays a sample of

Landsat 8 image tile for 15 April 2015 that covers Olushandja Dam.

The Digital Elevation Model (DEM) map covering the study area was obtained from USGS Earth Explorer <http://www.earthexplorer.usgs.gov> and four ground control points (GCP) were established. The dam outline and canal route were obtained by digitizing in Google Earth satellite image and converting to a shape file (.shp) format in Quantum Geographical Information system (GIS) or QGIS software. All files were then imported into ILWIS and were assigned to the same coordinate system as that of the study area.

The Landsat 8 imagery (cloud free or with cloud cover of <10%) over the area were selected for analysis. Radiometric Calibration to convert Digital Numbers (DN) values to physical units, at sensor spectral radiance (Watts/(m²/srad/μm)) and then to Top-of-Atmosphere (TOA) Reflectance was done in a GIS software, Environment for Visualizing Images (ENVI 5.0.3) using the same

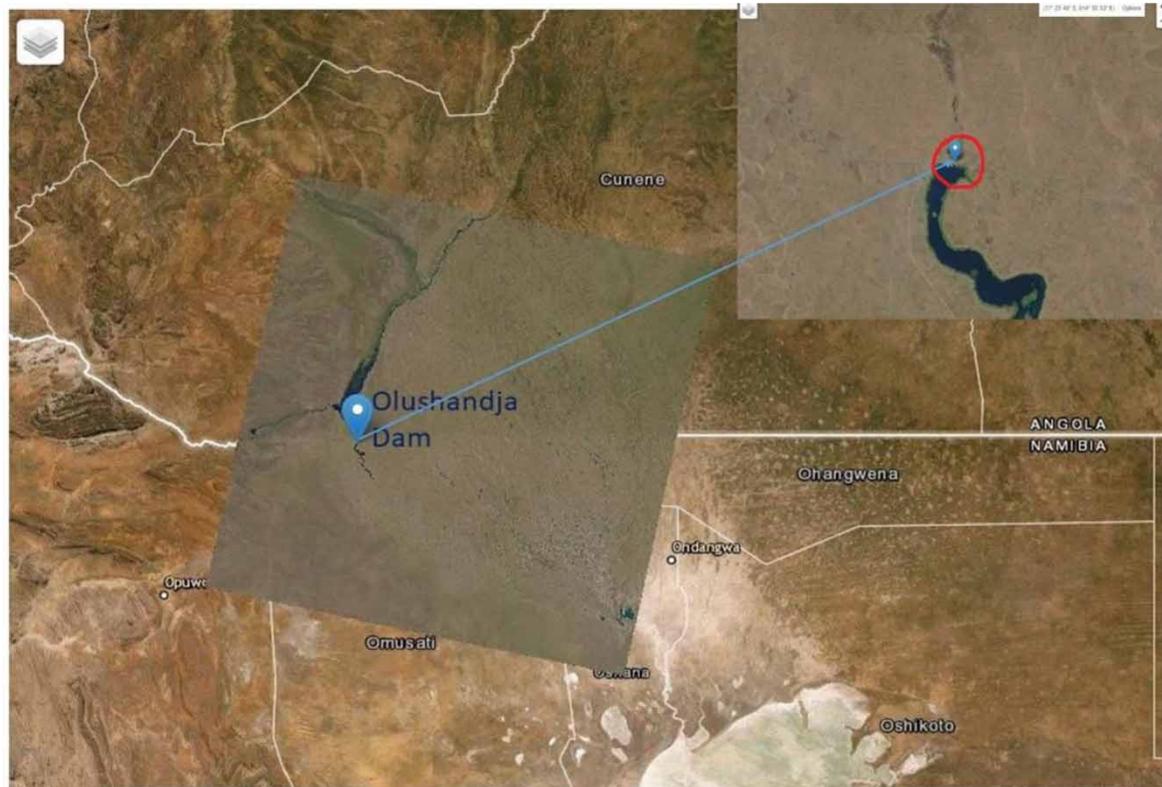


Figure 3 | Landsat 8 image tile of path 180; row 072 showing the location of Olushandja Dam.

equations described by [Chander *et al.* \(2009\)](#) and [USGS \(2013\)](#). In ENVI program, a band math expression was applied to rescale the floating reflectance value to surface reflectance of between 0 and 1.

After the radiometric calibration and atmospheric correction, pre-processed bands with reflectance were imported in the Integrated Land and Water Information System (ILWIS) GIS environment. The image raster maps were geometrically corrected by using the Nearest Neighbour resampling technique and assigning the correct georeference as that of the study area. This study used pixel reflectance values for the four visible and near infrared bands (2,3,4 and 5) of Landsat 8 images for each selected date based on the GPS locations of every sampling point. This was done in ILWIS through the 'map cross' operation that match-up sampling point raster map with a raster map of each processed bands (after image re-sample). Reflectance values of each band on every image at specific sampling point were determined.

Development of algorithms

The algorithms were then developed through a simple linear regression analysis to determine the best fit model. The surface reflectances of each band and water quality parameter values at a specific sampling point were regressed. Reflectance values of all bands were selected to be independent of each water quality variable. Independent variables that form relationship with reflectance by showing a high coefficient of determination (R^2) were selected based on literature ([Alparslan *et al.* 2007](#); [He *et al.* 2008](#); [El-Saadi *et al.* 2014](#)). The R^2 compares estimated and actual y-values, and ranges in value from 0 to 1. A value of 1 denotes a strong correlation in the sample, meaning there is no difference between the estimated value and the actual value. On the other extreme, if the coefficient of determination is 0, the regression equation is not helpful in predicting a y-value ([Alparslan *et al.* 2007](#)).

Application of the algorithms and validation

The developed algorithms were applied to resampled multi-spectral reflectance image bands. Interpolation was performed on the 6 sampling locations to come up with a spatial variation map of each parameter. The Inverse Distance Weighted interpolation (IDW) (Parida *et al.* 2017) technique was used for interpolating water quality data at respective point locations to grid points for comparison with satellite retrieved estimates.

Furthermore, the predicted values for each parameter were extracted from every parameter satellite raster map based on GPS location. The predicted values were validated against field measured data to test whether the satellite-based predictions were able to estimate water quality parameters. This was done by simple regression analysis using field data (for 25 January and 10 February 2015) that were randomly selected from main dataset and not used in the development of the algorithms to reduce errors. To assess detailed spatial distribution of water quality in Olushandja Dam, quantitative attribute maps were produced by applying algorithms to the original Landsat datasets.

RESULTS

Field measured data

The mean field measured water quality parameters data acquired from four sampling campaigns (26 Feb-15 April 2015) were calculated at each of the six points. The field data that correspond to the same dates as the satellite data (Table 1) are eventually used for model development.

Remote sensed data

The spectral band reflectance values at each sampling point on selected four images corresponding to field data (26 February and 15 April 2016) are given in Table 2. From the table, low reflectance values (<0.1) on the water body can be noticed and this could be due to the fact that water is relatively clean and this make it have low reflective spectral radiation (He *et al.* 2008).

Table 1 | Average values of measured data for four sampling campaigns at 6 sampling points in Olushandja Dam

Sampling Point	Algae counts (cells/ml)	Turbidity (NTU)	NH ₃ (mg/L)	TN (mg/L)	TPU (mg/L)	TSS (mg/L)
1	380	18.70	0.10	0.90	0.19	11.75
2	590	9.88	0.02	0.93	0.04	4.50
3	2,374	5.97	0.02	0.95	0.04	6.13
4	684	19.74	0.33	1.42	0.06	22.88
5	864	10.77	0.02	1.03	0.05	6.33
6	3,028	54.97	0.06	3.78	0.36	27.20

Note: NH₃ = Ammonia, TN = Total nitrogen, TP = total phosphorus and TSS = total suspended solids.

Table 2 | Average spectral band reflectance for four sampling campaigns at 6 sampling points in Olushandja Dam

Sampling Point	Band2	Band3	Band4	Band5
1	0.011	0.042	0.035	0.095
2	0.016	0.047	0.026	0.020
3	0.059	0.057	0.057	0.057
4	0.004	0.012	0.012	0.008
5	0.010	0.050	0.027	0.015
6	0.000	0.004	0.024	0.004

Developed algorithms

Field measured data (Table 1) were regressed with reflectance values (given in Table 2) using a simple linear regression method and algorithms were formulated and given on Table 3. Looking at the R² (coefficient of determination) and F-values (which approaches 1 for good performance), the results of regression analysis can be interpreted as follows; all the derived regression models have good regressive correlation for all parameters (i.e. total algae, turbidity, TN, TP, TSS and NH₃). Total algae, turbidity, TN, TP and TSS had R² values of 0.999, 0.986, 0.987, 0.980, 0.988, and 0.917 respectively. The R² values show that there is a high accuracy in predicting all the water quality parameters for the whole dam.

The R² values for all water quality parameters were high and close to 1, which shows that there is a significant relationship between satellite data and insitu-observed measurements.

Table 3 | Derived retrieval algorithms for each parameter through regression analyses

Water quality variable	(R ²)	Derived Algorithms
Algae	0.999	$= -54.7081 - 26766.6(\lambda_2) - 42687.5(\lambda_3) + 137000.1(\lambda_4) - 23819.7(\lambda_5)$
Turbidity	0.986	$= 15.31856 - 956.806(\lambda_2) - 747.376(\lambda_3) + 1742.455(\lambda_4) + 165.173(\lambda_5)$
TN	0.987	$= 1.047532 - 54.928(\lambda_2) - 46.2947(\lambda_3) + 120.8943(\lambda_4) - 19.223(\lambda_5)$
TP	0.98	$= -0.00309 - 8.78139(\lambda_2) - 4.99958(\lambda_3) + 15.31713(\lambda_4) - 0.3916(\lambda_5)$
TSS	0.988	$= 27.08987 + 10.80036(\lambda_2) - 507.708(\lambda_3) + 95.37331(\lambda_4) + 27.8424(\lambda_5)$

Note: TN = Total nitrogen, TP = total phosphorus and TSS = total suspended solids. λ = pixel reflectance values at band 2–5.

The F value in one-way analysis of variance (ANOVA) aided in assessing whether the variance between the means of Landsat 8 derived water quality values and field measured water quality relate. Calculated F-values (not displayed) show that all algorithms exceeded the 95% level of confidence. Li (2009) also found algorithms for turbidity in Shakespeare Bay to exceed 90% confidence level. Furthermore, NH₃ showed no significant correlation with satellite data and had low F-value (less than 4.53), thus it was excluded in the prediction.

Prediction of water quality parameter from satellite data

The study demonstrated that all four bands of Landsat 8 data contribute to derived water quality parameters. The equations in Table 3 were applied to multispectral Landsat datasets to predict water quality parameters over the entire dam and at each sampling point. Five water quality variables in Olushandja Dam (turbidity, total suspended solids, nitrates, ammonia, total nitrogen total phosphorus and total algae counts) were derived from Landsat 8 imagery on 26 February, 14 and 30 March as well as 15 April 2015 (four sampling campaigns). This was done after applying the developed algorithms to original bands with surface reflectance and summary statistics (Table 4) and spatial distribution (Figure 4(a)–4(e)) of the predicted five water quality parameters are presented.

Spatial variation of predicted water quality parameters

The resultant quantitative maps for the five water quality variables (total algae content, turbidity, and concentration

Table 4 | Summary statistics of predicted water qualities over the entire Olushandja Dam

Statistics	Concentrations				
	Algae (cells/ml)	Turbidity (NTU)	TN (mg/L)	TP (mg/L)	TSS (mg/L)
Minimum	0	4.7	0.00	0.00	0.0
Maximum	21,204	356.0	13.20	2.60	42.0
Average	1,650	83.2	1.39	0.43	8.8
Standard deviation	3,143	63.2	2.18	0.40	16.3
NamWater	–	5	–	–	–
Canadian	–	50	–	–	–
UN/ECE	–	–	< 300	< 10	–

of total nitrogen, total phosphorus and total suspended solids) are presented in Figure 4(a)–4(e). The resultant maps clearly show that different water quality parameters yield several spatially distributed patterns over the reservoir over time. Some parameters show very low predicted values, especially in areas with dense vegetation in the inner and along the edge of the dam closer to the land and some show the opposite. This can be due to reflectance ability of specific bands, especially band 5 (near-infra red) that reflect high on vegetation and interaction of water and land than in water (USGS 2013).

The resultant maps demonstrated that total algae contents and concentrations TN, and TSS are highly variable over the dam while turbidity and TP had less spatial variance. Turbidity is found to be above recommended limits of drinking water standards by NamWater as well as for recreational purpose of the Canadian (50 NTU). Other studies (He *et al.* 2008; Li 2009; Lehmann 2010) found high turbidity levels in different water bodies. Total nitrogen and total phosphorus

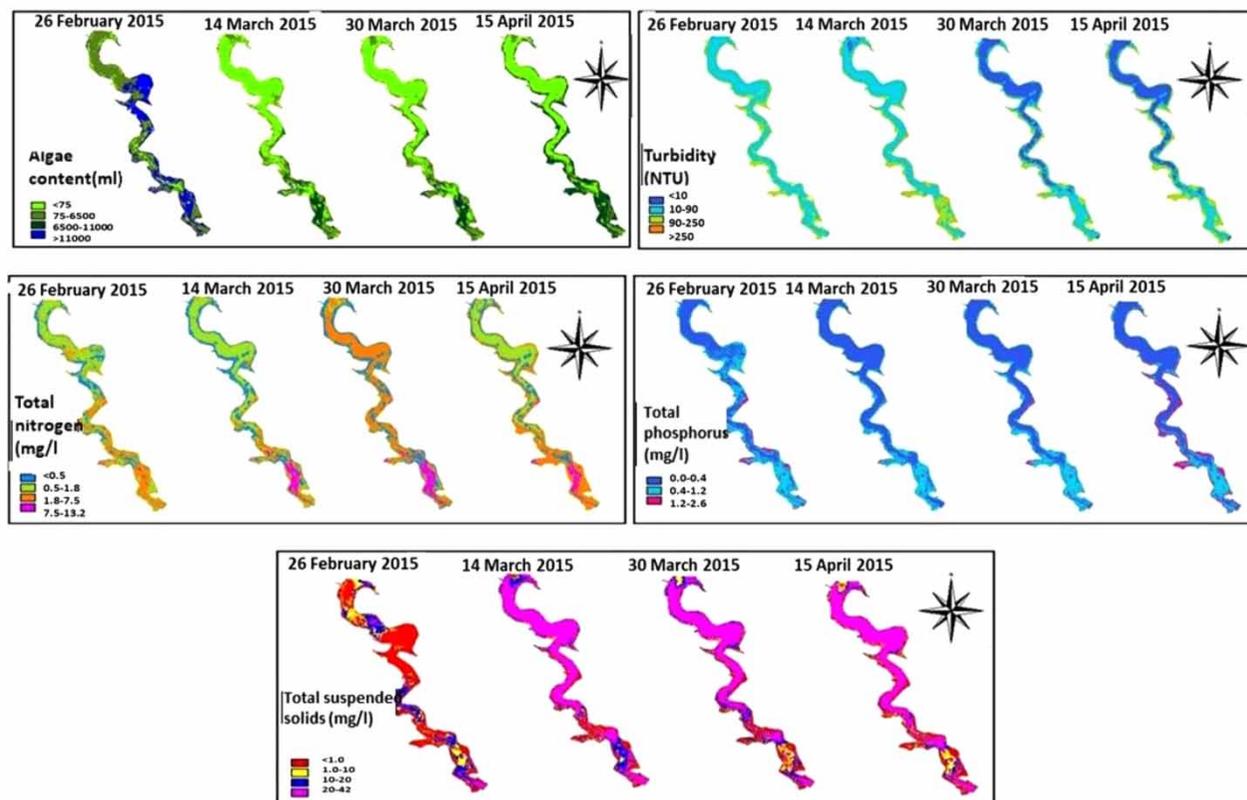


Figure 4 | Spatial variation of predicted water quality parameters.

values are found to be within the [UNECE \(1994\)](#) standards for maintaining the aquatic life which <300 mg/L.

Validation of algorithms

The relationship between Landsat predicted values and insitu-observed measurements of water quality parameters at each of the 6-sampling points for 15 April 2015 are presented in [Figure 5\(a\)–5\(e\)](#). Turbidity, TN, and TP and total algae count showed medium to strong positive linear relationship between Landsat predicted and measured while TSS showed a weak linear relationship. The regression coefficients between predicted and measured values were: turbidity ($R^2 = 0.767$); TN ($R^2 = 0.798$); TP ($R^2 = 0.907$); TSS ($R^2 = 0.284$) and total algae count ($R^2 = 0.851$). Total suspended solid showed a low coefficient than all other parameters. Looking at R^2 values, it can be concluded that prediction models are best fit to derive the four water quality parameters except TSS.

[Figure 5\(a\)–5\(e\)](#) confirms the strength of the regression models by showing correlation with high coefficient of determination (R^2) between predicted values and measured data. It was found that TP has higher R^2 followed by total algae counts, TN and turbidity respectively. TSS had a low correlation coefficient.

Methodological framework for monitoring water quality

Based on the result of this study, Landsat data has proven its ability to derive water quality parameters, data that are comparable to the insitu-observed measurements. Therefore, a proposed a framework for predicting water qualities for Olushandja Dam is presented in [Figure 6](#).

The framework will help responsible institutions such as NamWater and Department of Water Affair under Directorate of Resources Management in the Ministry of Agriculture, Water and Forestry and interested

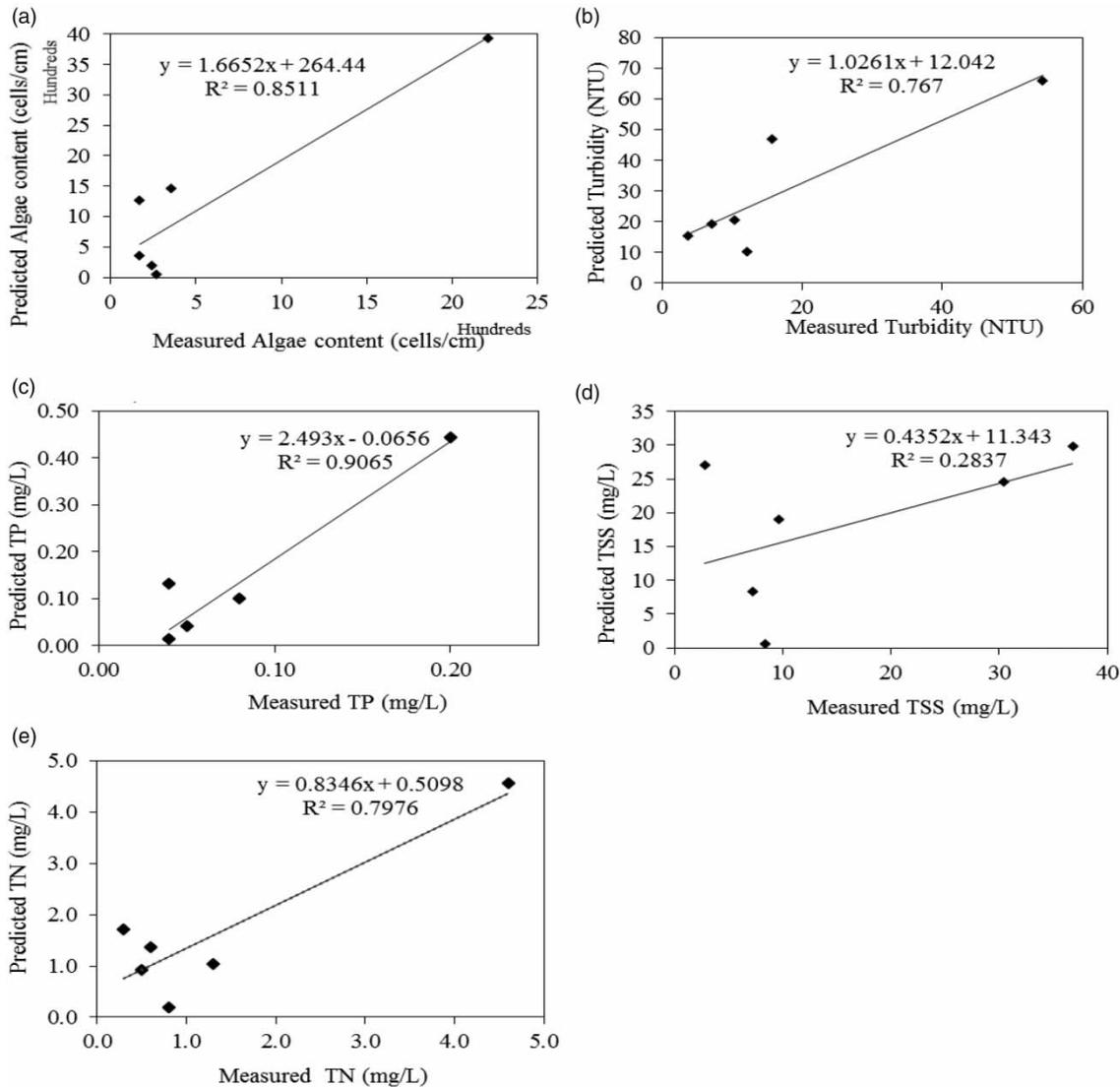


Figure 5 | (a–e): Relationship between Landsat predicted versus field measured data. Note: (a) Total algae content, (b) Turbidity level, (c) Total nitrogen (TN), (d) Total phosphorus (TP) and (e) Total suspended solids (TSS).

members of the community to implement a continuous monitoring of water quality for improved decision-making. The framework will also be useful to Ministry of fisheries as there are fishery resources, Ministry of Health and Social Services, students, community members, water resources managers, planners, developers and any other interested parties. The application of this framework would require among others: personnel with some knowledge of GIS and Remote Sensing; financial resources (for transportation and laboratory costs).

DISCUSSION

Summary

This research found that regression analysis-based retrieval algorithms are ideal for water quality retrieval in Olushandja Dam, North-Central Namibia. Obtaining the spatial variation of water quality parameters allows decision makers to manage the critical resource in near real time. Remote sensing is therefore recommended for frequent and continuous monitoring of Olushandja Dam as it has the ability to

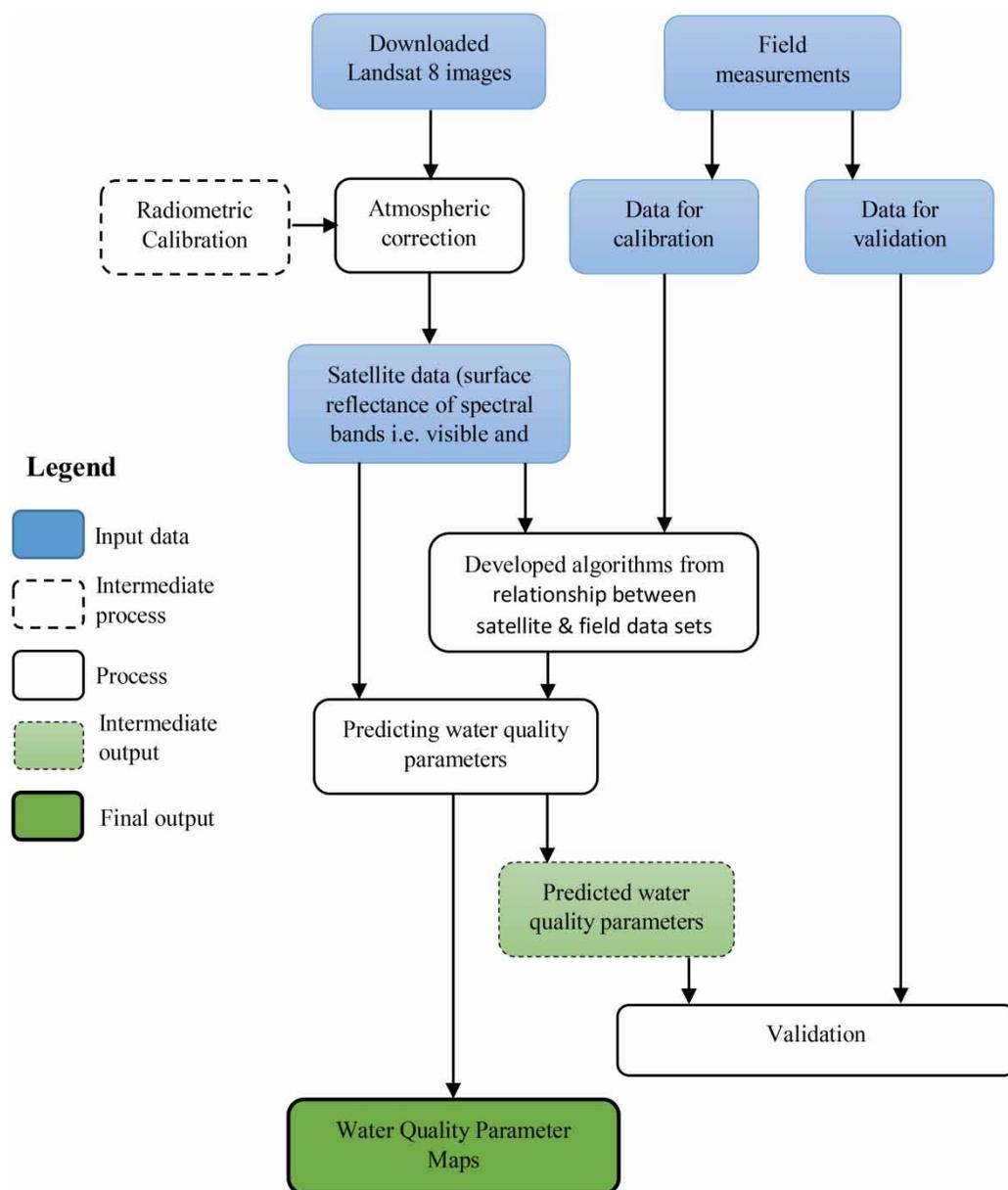


Figure 6 | A proposed framework for predicting water quality parameters based on remote sensing.

provide the information on the spatio-temporal variability of surface water quality. A detailed discussion and future applications of the present work are described in next sections.

Regression analysis-based algorithms for water quality retrieval

Insitu based water quality retrieval (Bhuyar *et al.* 2019a, 2019b) bring limitation in comprehensive water quality

assessment. This study used Landsat 8, 30 m spatial resolution imagery's reflectance values and insitu-observed data to develop regression analysis-based retrieval algorithms from November 2014 to June 2015. The study found that the majority water quality parameter regression algorithms had high correlation coefficients (R^2) between 0.75 and 0.99. Therefore, the study concludes that the developed regression algorithms are best fit to predict water quality parameters from satellite data. The study further applied the

developed algorithms to derive water quality parameters at selected points in the dam. Correlation analyses was performed between Landsat 8 predicted and field measured data (Masocha *et al.* 2018). Alparslan *et al.* (2007) used Landsat ETM pixel reflectance at Ömerli Dam, which is a vital potable water resource of Istanbul City, Turkey and also found suspended solid matter and total phosphate to have high R^2 of 0.9999 and 0.9906, respectively. On the other hand, Reza (2008) showed that there is a relationship between the level of suspended solids and MODIS radiance or reflectance in the seawater region around Penang Island of northern Malaysia. Lim *et al.* (2008) revealed that the Total Suspended Solids (TSS) algorithm developed in the same island (Penang) from optical properties is a promising TSS model for high-accuracy TSS mapping using satellite data. Furthermore, He *et al.* (2008) found a fairly high correlation between Landsat TM imagery DN values with water quality variables (algae, turbidity, TN and TP) at the Guanting Reservoir in Beijing, China. All the above studies have concluded that water quality can be successfully derived through remote sensing data. Our study shows that there is generally a good correlation for all the parameters except total suspended solids suggesting that the algorithms can be used to retrieve and predict water quality data.

Spatial variation of retrieved water quality parameters

The spatial distribution of water quality parameters retrieved from satellite data demonstrate similar patterns as the in-situ-observed measurements based on a statistical comparison (R^2 of >0.75 except for total suspended solids). Hafeez *et al.* (2019) found similar results with turbidity amongst other parameters, in a comparison of satellite retrieval of reflectance data with *in situ* reflectance data for a study in Hong Kong. The results of this study show that there is substantial spatial variation in the concentration of water quality parameters both longitudinally and latitudinal due to several factors. These include rainfall runoff processes (Bonansea *et al.* 2015), nutrient accumulation due to decomposition of plants and animals as well as low or no flow especially at end part of the dam. In addition, it could be due to human activities such as fishing, abstraction of water and swimming which would encourage mixing of water constituents. All these factors affect water quality.

In addition to the 6 sampling points, the Landsat predicted data at specific sampling points were also compared to water quality standards for the different uses. Turbidity was found to be above the NamWater (1998) of 5 NTU but below the Canadian (2012) guidelines for recreational water quality (50 NTU). On the other hand, TN and TP are below ECE (1994) standards for maintenance of the aquatic life which is <300 mg/L and <10 mg/L respectively. Water quality parameters outside recommended ranges are likely to cause complications in drinking water treatment as well as human and aquatic life.

Suitability of medium resolution satellite images for water quality monitoring

This study proves that medium resolution images such as Landsat are able to predict water quality parameters based on high regression coefficients (>0.75) as observed in studies by Alparslan (2007), Concha & Schott (2014), Chen & Quan (2012), He *et al.* (2008) and Hellweger *et al.* The study also showed that Landsat 8 has capabilities in modeling water quality of relatively clean water bodies which has a low spectral radiation just like Landsat TM as recommended by Peterson *et al.* (2020), Pu *et al.* (2019) and He *et al.* (2008). Li (2009), however, used different Landsat missions (Landsat 5) in the Chesapeake Bay, USA for water quality monitoring. However, the in-situ-observed measurements remain critical in the process of monitoring water quality using remote sensing techniques (Ritchie *et al.* 2003). Namibia has cloud free sky most times of the year which makes remote sensed water quality monitoring possible.

Future application of the present work

The future practical application of the present work includes the improved capacity to predict water quality status under data scarce environments such as North-Central Namibia where there is a deterioration of water quality. Such efforts potentially contribute towards improved environmental and watershed management in an integrated water resources management approach. Based on the strong relationship between field-based water quality results and satellite-based water quality

retrieval, our results also help in rapid water quality appraisals of other reservoirs in Namibia. In addition, the developed algorithms can be used to assess anthropogenic land use activities to pollution of reservoirs. Multiple linear regression analyses of landuse and landcover variable combinations can further be developed and used to develop equations for estimating water quality parameters. Example applications of such work can also be found in many global water resources studies (Christian *et al.* 2000; Goodman *et al.* 2020; Kim *et al.* 2020; Pasika & Gandla 2020; Topp *et al.* 2020). A water quality prediction framework for Olushandja Dam, North-Central Namibia will continue to use freely available earth observation data to contribute towards improved management of pollution. Future work should also focus on developing a mobile based and a web-based application for rapid retrieval and communication of the water quality information.

CONCLUSIONS AND RECOMMENDATIONS

The capacity to predict water quality status under data scarce environments can potentially contribute towards improved water quality management. The study demonstrated that a linear regression statistical approach can be used to develop algorithms for retrieving water quality data from satellite imagery as the correlation between the water quality values retrieved from remote sensing techniques had a high correlation with field measured data ($R^2 > 0.98$). The algorithms developed have a good prediction accuracy for turbidity, total nitrogen, total phosphorous and total algae count as the linear relationship between Landsat predicted and measured values had R^2 of 0.77–0.91 while prediction for total suspended solids showed a weak linear relationship ($R^2 = 0.28$). The developed of algorithms can be used to predict water quality variables for the whole Olushandja Dam but require more sampling points to further improve the accuracy of regression models. We recommend further development of a GIS web-based application for rapid retrieval and communication of the water quality information by water managers, water users and stakeholders in the Cuvelai Basin in north-central regions of Namibia.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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