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MONITORING WATER QUALITY OF LAKE VICTORIA IN UGANDA THROUGH REMOTE SENSING

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ABSTRACT

Lake Victoria being a source of livelihood for millions of people in the great lakes region ensuing from the supply of water, fish, ecosystem management transport and recreation, its water has to be monitored both in quantity and quality. Its quality is negatively impacted by anthropogenic factors in the catchment area such as high rates of deforestation and wetland degradation due to agricultural expansion, repository for human, agricultural and industrial waste. The quality of the water is meant to be monitored at least once every three months by sampling water pollution estimates at several monitoring stations within the lake. For the years 2014 - 2017, this had not been the situation in Uganda since measurements were a year apart. Hence a major technical challenge facing management is the timely quantification of the lake's nutrient load. The current approach is limited in geographical extent and temporal resolution as well as costly in both time and other resources for the entire Eastern African region.
To address the timely data gap challenge, the research proposed the benefits of augmenting the current approach with Remote Sensing and GIS to monitor the catchment area and the lake ecosystem to deliver timely and cost effective information to management. Through regression analysis, optical remote sensing imagery and field data from off shore water monitoring stations were correlated and used to study spatial-temporal dynamics of water quality. Processes in the catchment area, such as industrialization, population growth and land use change, were considered as explanatory variables to changes in water quality.

The resultant regression models of water quality were key in understanding the past spatial temporal trends in water quality and also give insights into what is likely to happen in the future. Parameters for which models were designed are transparency and chlorophyll-a. Transparency exhibited R^2 of 0.67 at design and R^2 of 0.92 at validation stages. Modelled results indicated that for the entire lake transparency was improving since 1995 to 2015. Chlorophyll-a on the other hand, had ups and downs with the downward (deteriorating) trend being more significant after

2003. Taking a close look at specific locations up to 40 Km within the lake from the shoreline, the trend was more of a worsening nature as opposed to entire lake. Simulations of prospective events revealed that concentrations of chlorophyll-a are expected to continue to rise at a rate greater than 0.22 μgL^{-1} per year that was observed between 2003 and 2015 giving averages of 30 μgL^{-1} by year 2023. The hyperbolic rise is likely to be accompanied with lower fish catches and rise in water borne diseases. The quality of imagery remained the single most important factor determining usability of imagery for water quality.

Keywords: water quality, remote sensing, transparency, chlorophyll-a, Landsat, MODIS, Sentinel

1. INTRODUCTION

Majority of human civilizations and the survival of ecosystems have largely depended on the supply of fresh water which is in the range of only 3.5% and 2.5% distributed between all Earth's freshwater sources, including water vapor in the air, water in lakes, rivers and aquifers (USGS, 2016). The quality of surface fresh water is continuously on the decline, as witnessed by UNEP – GEMS due to issues amassing from: Metallic contaminants, Microbial pollution, Eutrophication (algal concentrations), Acidification, Excessive fishing and Many other human induced activities. These and challenges fostering cooperation in 63 trans-boundary water basins, prevention of land degradation alongside water pollution, as well as managing water resources under global climate change are common place in Africa aimed at improving the quality, quantity in addition to use of water on the continent UNEP (2010).

Eastern Africa region has close to 50% or more of the lakes on the African continent (Thomas *et al* 2014). And the biggest fresh water lake in Africa has a catchment shared by 5 countries (Kayombo and Sven 2006). Still in the East African region, the efforts to monitor water quality mainly concentrate on the water for consumption alongside other environmental issues as illustrated by initiatives like Lake Victoria Environment Management Project (LVEMP I and II) in the Lake Victoria catchment area.

Lake Victoria is a source of livelihood for millions of people in the great lakes region. This is due to the supply of water, fish, ecosystem management and transport. However, the anthropogenic factors in the catchment area such as high rates of deforestation and wetland degradation due to agricultural expansion, repository for human, agricultural and industrial waste have a negative impact on water quality (DWD, & WWAP, 2005). One major technical challenge facing management is timely quantification of water body nutrient load not only in Uganda but also elsewhere in the world (Thomas *et al*, 2014; Hellweger *et al*, 2004; Sudheer, Indrajeet, & Vijay, 2006; Sáenz, Paez & Arango, 2015; Kayombo & Sven, 2006; Juan *et al*, 2016) Traditionally, water pollution estimates are quantified by sampling at several monitoring stations within Lake Victoria at least four times a year (DWD, & WWAP, 2005). Due to budgetary and other constraints, the quarterly field visits had not been realized as exemplified by the last three measurements: 28th November – 7th December 2014, 4th – 13th October 2015 and November 2016 prior to 2017. Even then, not all the 19 offshore stations were accessed in a

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particular field visit. The current approach is limited in geographical extent and temporal resolution. The available data leaves little opportunity to predict quality behaviour beyond the point of field measurement in the medium as well as long term over the entire lake. This makes a holistically cost effective planning impossible as the quality of the lake reservoir is unknown for periods close to a year for example, from October 2015 to November 2016.

In 2017, regression analysis of in situ field measurements and satellite images from various sensors were compared to give the possibility of use of remote sensing in studying water quality and filling such gaps in Uganda. In this paper we report the findings of how it can be achieved.

2. DATA AND METHODS

2.1Study Area and Design

The study was designed around Lake Victoria as a surface water body on the side of Uganda with a lot of interest in chlorophyll-a (ChlA) and Secchi Disk Transparence (SDT) as characteristics of water quality. The spatial extent of Lake Victoria in Uganda is 28,148.10 Km^2 deviating from 31,000Km^2 quoted by Cheruiyot and Muhandiki (2014) due to perhaps exclusion of islands and working with a water mask that represented an area that was consistently water since 1990. Water clarity, and chlorophyll-a, as can be perceived from majorly Landsat satellite imagery, were of great interest as the key factors that guided the research. The main reason for emphasizing Landsat was because of the long historic archive that dates back to 1972/3. Figure 2.1 illustrates the extent of the study area and location of the sample sites within the study area. It can be noticed that not much can be discerned from a true color image except for conditions that have gone to extremes like on the eastern side of the lake in terms of water quality.

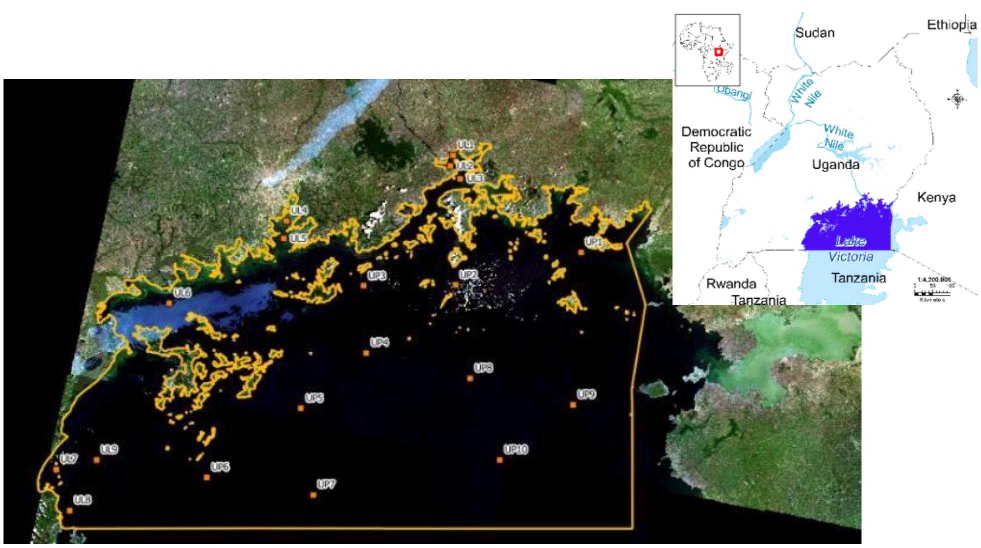

Figure 2 1 Study area with location of in situ measurements using a true color image as the background

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In-situ sample collection and image acquisition

In situ Water Quality characteristics/measurements collected in October 2015 by DWRM were used statistically to correlate with Landsat images of February. Image acquisition was realized through Earth explorer a United States Geological Surveys (USGS) web portal. The main satellite sensors used were Landsat series. Compressed Surface Reflectance images of choice were downloaded for analysis. These included Landsat 5 for images of 1995 and 2009; Landsat 7 for images of 2001 and 2003; and Landsat 8 for 2015. Images for years in between were not used due to cloud cover and haze. The same factors posing analytical challenges for images that were downloaded. MODIS and Sentinel were only used for comparison and assess possibility of both historic and future use respectively. Besides, extensive work had already been done with MODIS previously by Banura *et al* (2012) and Todd *et al* (2010). Seven Sentinel 2A tiles (granules) each covering an area of 100 Km by 100Km for 2016 and 2017 were downloaded to explore and determine their usage within the study. The tiles were accessed through the European Space Agency or ESA scientific hub web site and earth explorer of USGS.

Image Processing

When downloaded, the images are uncompressed and bands suitable for water quality studies were selected for stacking into image composites. The composites were mosaicked to cover the entire Lake Victoria and then sub set for the area in Uganda. Land from imagery data was masked out to enhance the less than 5% spectral reflectance or Specific/Inherent Optical Properties (SIOP) exhibited by water.

MODIS data for dates corresponding to Landsat plus Sentinel acquisition dates was downloaded to investigate how water quality parameters compare across sensors. MODIS and Sentinel imagery could also be used to show the possibility of assessing daily, weekly and monthly as well as seasonal variation due to their superior temporal resolution of twice a day and every five days respectively. Any images that did not correctly register with their respective global positions were to be geometrically corrected to achieve conformity.

Since MODIS offers Level 2 products ready for consumption (use) and analysis through Land Processes Distributed Active Archive Center (LP DAAC) and ocean color web page, these were downloaded in preference to the raw bands. Unfortunately, none of the products catalogued were for SDT.

In order to use these MODIS products, they had to be sub set first for the bands containing chlorophyll-a and location flags using ESA - SNAP 5.0 re-projection tools. After sub setting, they were projected from the native projection to WGS 1984 UTM and exported into GEOTIFF image formats. Finally, the chlorophyll-a band was extracted using the lake boundary as the mask for the different time periods using ArcGIS 10.2.2.

Sentinel optical imagery with comparable spectral ranges to Landsat were available after June 2015. By the time of study, European Space Agency (ESA) provided level – 1C processed products for Sentinel – 2 that are corrected for top of Atmosphere (TOA) reflectance. These were processed into 2A products Bottom of Atmosphere (BOA) or surface reflectance (SR) by using Sen2Cor ESA - SNAP plug-in.

Correlation analysis and regression models

After image processing, mathematical models were used to establish relationships between in situ measurements and satellite data of land masked imagery in MS-Excel 2013 for off shore monitoring stations. A data set in which all 19 off shore stations were visited for the year 2015 was preferred. The models were generated through regression analysis. Regression analysis was achieved through activating Data Analysis Add-in. A critical value of $P < 0.05$ was used to reject the null hypothesis at a p-value of 2.87×10^{-6} for Chlorophyll-a and 1.13×10^{-5} for SDT. Regression analysis was still employed to test the reliability and validity of the models for water quality investigations.

The models were used to establish past trends thus giving insight into future scenarios after determining annual rate of change in ChlA and SDT from the shoreline inwards of the lake.

Open Foris Geospatial Toolkit (OFGT) was used to prepare the imagery for subsequent manipulation. MS - Excel 2013 and QGIS were used to calculate logarithms from Landsat and Sentinel 2A Surface Reflectance values. The resultant logarithms were converted to their respective water quality prediction measurements in the same environments. MODIS did not require rigorous data preparation since ready to use products were downloaded for Chlorophyll-a.

Data Visualization

ArcGIS and QGIS were used to visualize the data during manipulation steps all the way from data preparation to data analysis and presentation of results.

ERDAS 2016 and ArcGIS 10.2.2 were used to classify or model data into different ranges of water quality parameters using the legend and raster reclassification tools after studying data histogram distributions.

3.RESULTS

19 of 56 off shore water quality monitoring stations on Lake Victoria are in Uganda. Among many of the water quality measurements examined at these stations include Chlorophyll –a and Secchi Disk Transparency. The units of measure for these characteristics are microgram per liter (μgL^{-1}) and meters (m) correspondingly.

From over 40 Landsat image choices, the bands used were mainly the blue and red bands more specifically from Landsat and Sentinel. For the year 2015, almost cloud free images gotten were for January, February and July. This is usually the time before the Rainy Seasons of March to May and September to November respectively. To determine relationships between variables, logarithms of water quality measurements were linearly correlated with logarithms of either red or logarithmic ratio of blue and red bands for SDT and ChlA correspondingly.

Models Secchi Disk Transparency

The log of Secchi Disk transparency was correlated to the log of red band to estimate transparency using equation 1 below with a coefficient of determination, R of 0.79 and coefficient of regression, R^2 of 0.63. This was achieved at 95% confidence with a standard error (SE) of 0.15 and 19 observations.

$$logSDT = 2.45944203061747 + (-0.980448607181891 * log10\ (\text{“}Red\ Band\text{”}))\ldots \text{equation 1}$$

The above equation can be written as

$$y = 2.45944203061747 - 0.980448607181891x \ldots\ldots\ldots\ldots\ldots\ldots \text{equation2}$$

Where 2.45944203061747 is the y - intercept and -0.980448607181891 is a constant required by the x – variable. The x (independent) variable being the log of the red band while y (dependent) variable is logSDT. Comparing the measured against the predicted SDT generates figure 3.1.

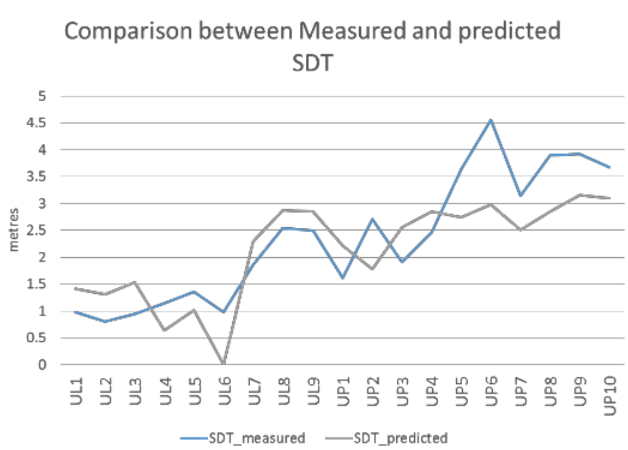

Figure 3 1 Measured viz Predicted

All the above were achieved without dealing with confounding factors like outliers and no data values as well as residual clouds in in-situ and image data.

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Chlorophyll – a

The log of Chlorophyll-a was correlated to the ratio of log blue to log red band using equation 3 below with R of 0.85 and R^2 of 0.72. This was realized at 95% confidence with a SE of 0.3 and 18 observations.

$logChlA = 8.24040612923062 + (-7.19921986841488 * (log10\ ("Blue\ Band")/log10\ ("Red\ Band"))$ ………………………………………………………………… equation 3

Equation 3 can be written as

$y = 8.24040612923062 - 7.19921986841488x$.... .... equation 4

Where 8.24040612923062 is the y - intercept and 7.19921986841488 is a constant required by the x – variable. The independent variable or x is the blue and red band log ratio while the dependent variable or y is logChlA. Comparing the measured against the predicted SDT generates figures 3.2.

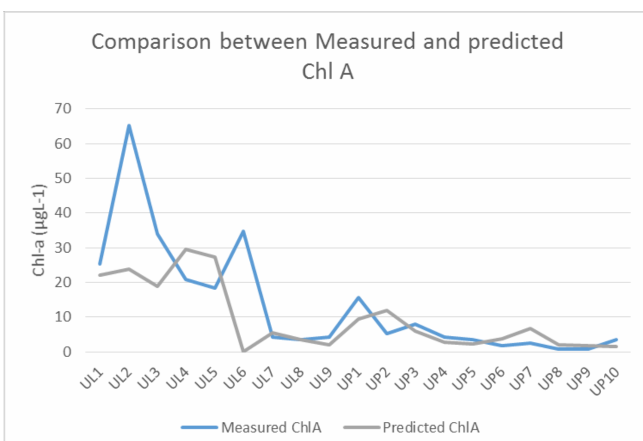

Figure 3 2: Measured viz Predicted

Model validity

To test the validity of the models over time, data measured on the lake that was not previously used either in the model development nor imagery analysis were utilized independently. Several years were used to remove bias of year or sensor of acquisition. To remove effects of confounding factors, areas with cloud influence within the images were avoided and so did areas that had no data (gaps) as was the case with Landsat 7 ETM. Sample locations that lacked in situ measurements were also not used in validation process.

Sechi Disk Transparency

When validating the model in equation 1, the resultant image estimates were plotted against in situ measurements for the corresponding years. Using regression analysis, the modelled and measured values correlated with R^2 of 0.92 at 95% confidence interval. The equation below provides the model under validation testing with a SE of 0.37 among 32 observations again:

$$logSDT = 2.45944203061747 + (-0.980448607181891 * log10\ (\text{“}Red\ Band\text{”})$$

The figure 3.5 shows line of best fit for the datasets.

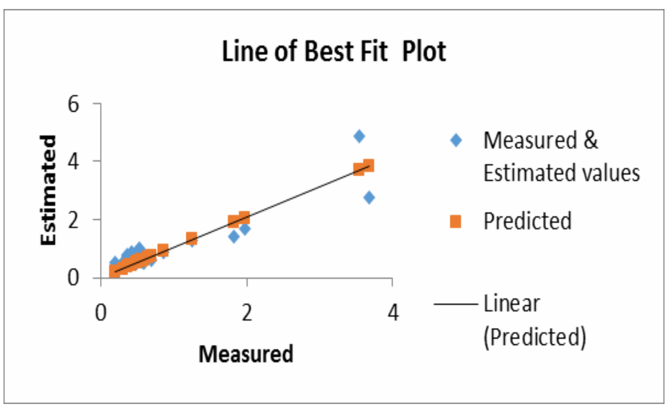

Figure 3 3 Line of best fit for Transparency

Chlorophyll-a

Like Transparency, chlorophyll-a underwent regression analysis and the results were more reliable compared to clarity despite the huge SE. The R^2 of modelled and measured values was equal to 0.99 with a SE of 1.13 at 95 % confidence and 14 observations. There were not as many historical observations for chlorophyll-a as transparency which might be the likely explanation for the high R^2 and ES. The model under validity testing is here again presented for chlorophyll-a. The graph that follows illustrate outputs of the regression analysis.

$logChlA = 8.24040612923062 + (-7.19921986841488 * (log10\ ("Blue\ Band")/log10\ ("Red\ Band"))$

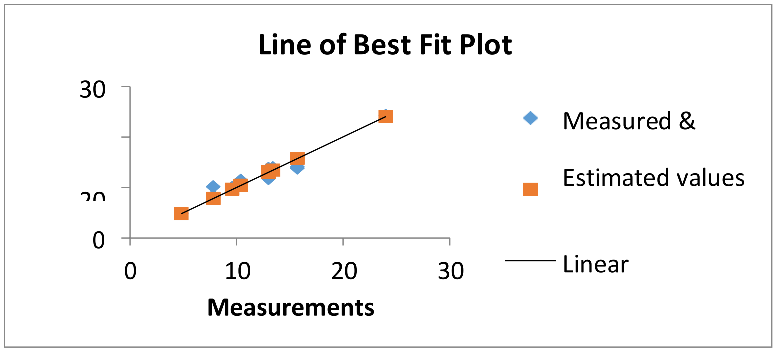

Figure 3 4: Line of best fit for Chlorophyll-a

4. ANALYSIS

Secchi Disk Transparency Landsat

For the period 1995 to 2015, there is an overall improvement in transparency over the entire lake as can be appreciated from the graphs in figures 4.1 and 4.3. One can also discover that some areas within the lake had portions where light could penetrate to depths greater than 4m in the years after 2000 and before 2015 as shown spatially and temporally in the maps series of figure 4.2 and charted in figure 4.1. The lowest mean of 1.25 meters having been observed in 1995 while the highest average of 2.36 was realized in 2015. Areas close to the shower line on the whole had lower SDT readings than far off shore for all years. In all cases from 1995 to 2015, clouds partly influenced some of the low transparency readings. Accordingly, the lake seems to be becoming clearer and it faced its worst clarity situation in 1995.

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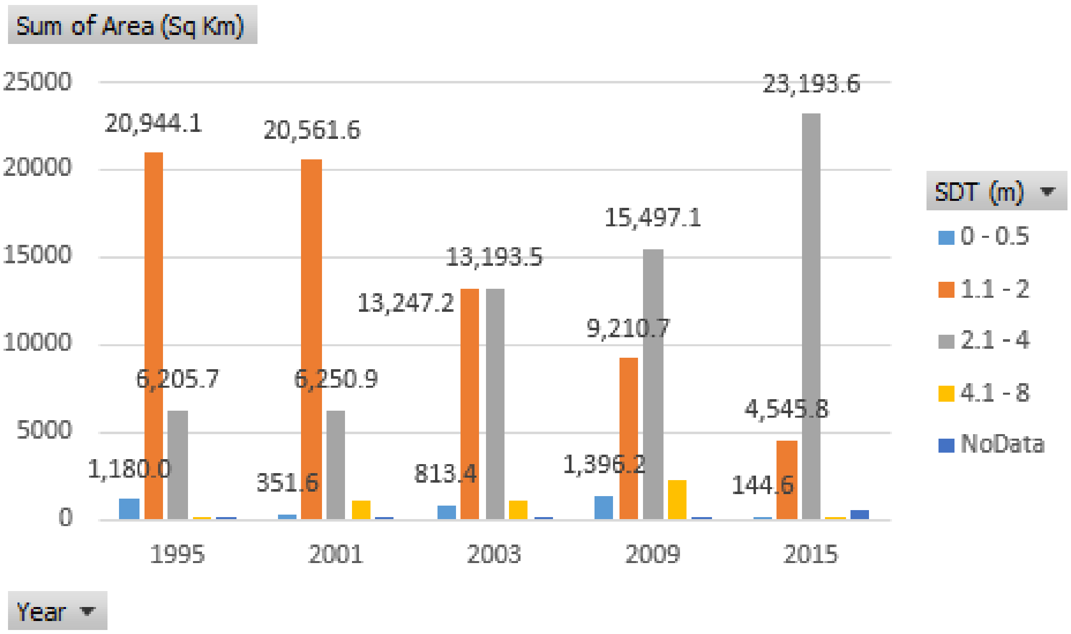

Figure 4 1 Simplified histograms of transparency from 1995 to 2015 together

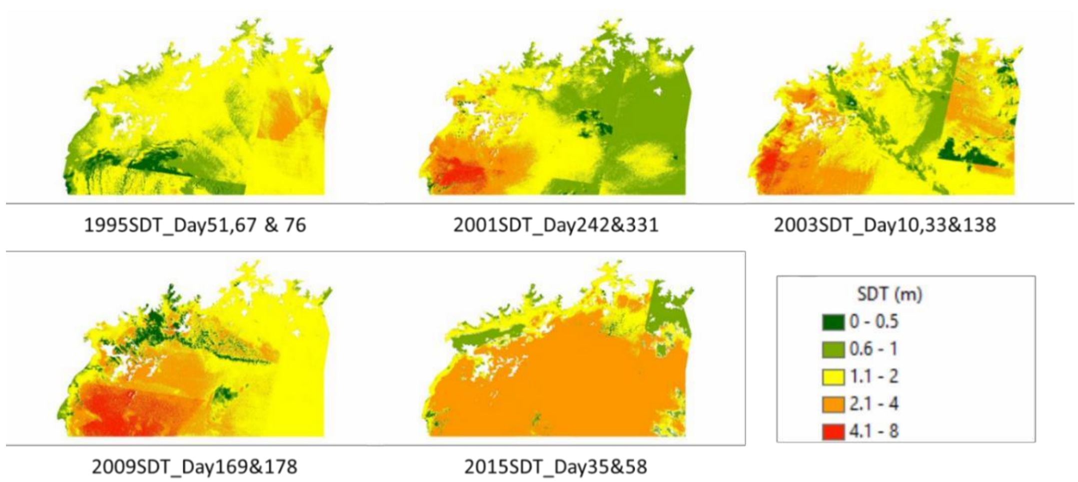

Figure 4 2 Secchi Disk Transparency trends from 1995 to 2015 with Landsat

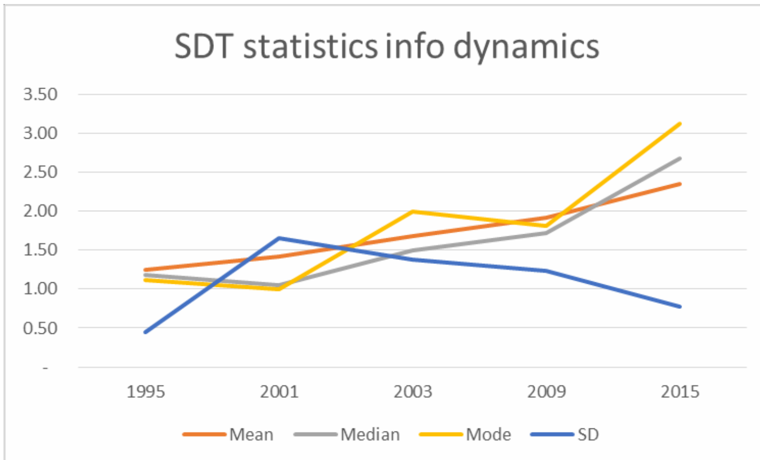

Figure 4 3: Trend lines of SDT from 1995 to 2015

Contrary to what the central measures are depicting for the entire lake, at particular transects the story defers slightly. Figures 4.4 details this divergent version. By intervals of 4 Km from the shoreline, transparency averaged at 1.08 m in 1995, 1.15m in 2001, 2.02 m in 2003, 1.18 m in 2009 and 1.15 m in 2015. Showing a rise from 1995 to 2003 and currently on a downward trend. The behaviour at each particular location is shown in figure 4.4. The transects were of differing lengths 43.7 Km, .19.2 Km and 13.9 Km.

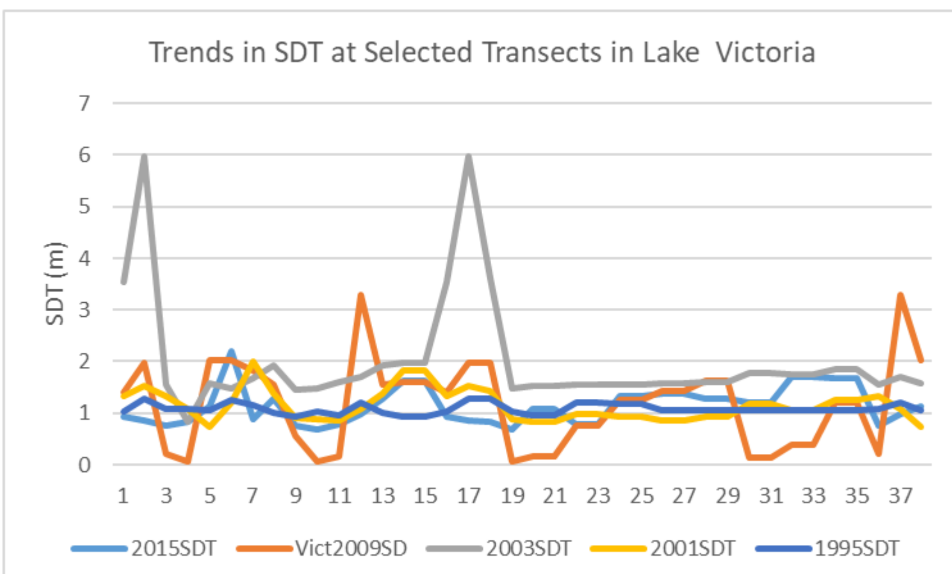

Figure 4 4 Trends in SDT from 1995 to 2015 for transects lines

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Sentinel

For consistence and similar to Landsat, bands 2 ,3, 4 and 8 that correspond to Blue, Green, Red and Infrared respectively were used for water quality assessment. Their spatial resolution is 10 meters yet that of Landsat is 30 meters. Of the downloaded images (2016 and 2017), only 2017 images responded to analytical manipulation of the model. Figure 4.5 indicates that more than 60% of the lake had SDT between 0.6 and 1 m depth. A small portion had transparency more than 4 m deep. Again some of the readings less than 0.6 m were attributable to cloud cover in some areas of the lake. Image statistics express the mean depth, median and the mode to have been 3.92 m, 0.96 m and 0.9 m correspondingly for the entire lake.

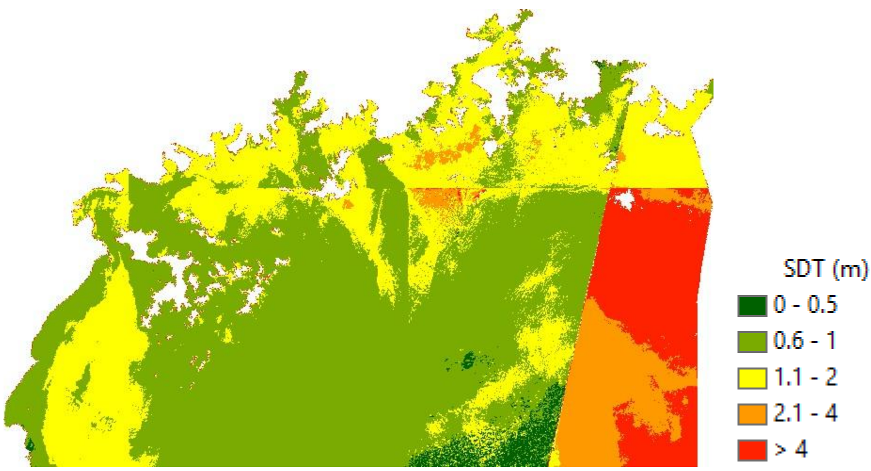

Figure 4 5 Secchi Disk Transparency 2017 from Sentinel 2A - 2017-01-12 & 25

Chlorophyll-a

Landsat

From 1995 to 2015, 2015 had the greatest concentration of chlorophyll-a along the shoreline. And if it were not for the cloud contamination, it is possible the entire shoreline exhibited readings greater than 20 μgL^{-1}. Figures 4.5 and 4.6 represent the same information in terms of spatial and areal distribution during the study period while figure 4.6 shows behaviour of measures of central tendency.

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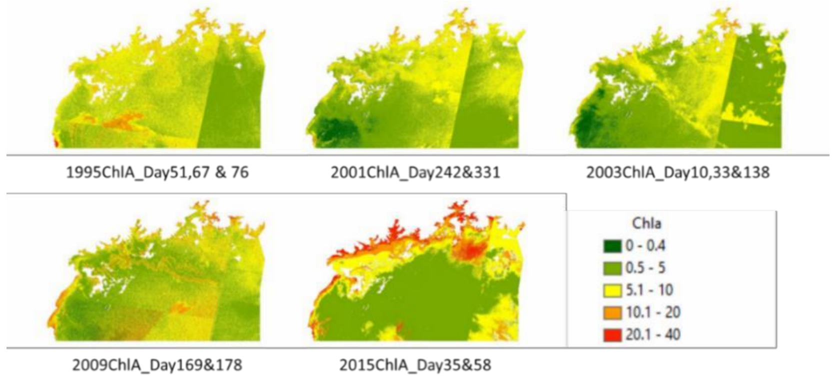

Figure 4 6 Chlorophyll-a trends from 1995 to 2015 with Landsat

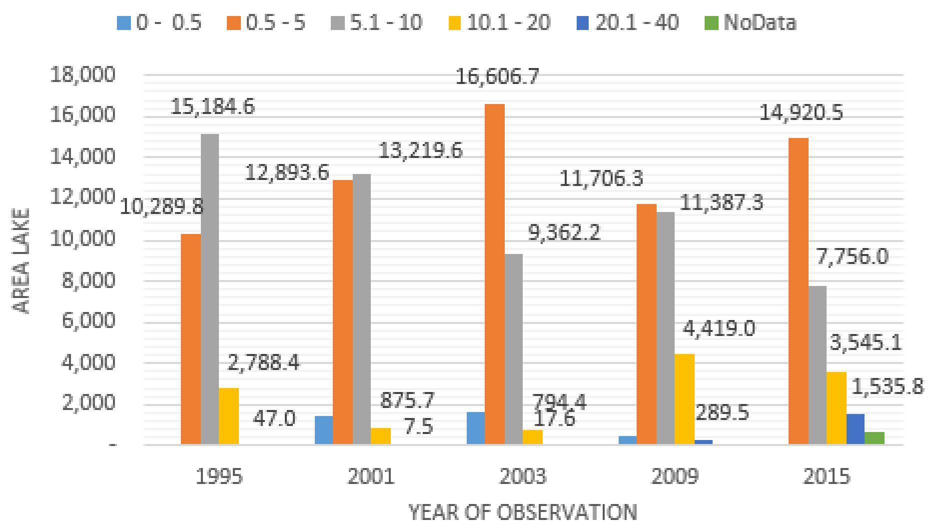

Figure 4 7: Simplified histograms of chlorophyll-a from 1995 to 2015 together

Chlorophyll-a

Concentrations were generally reducing (improving) steadily by roughly a whole μgL^{-1} between observation epochs (5.78 μgL^{-1} in 1995, 4.85 μgL^{-1} in 2001) before 2003 (3.85 μgL^{-1}) and increased thereafter to a mean of 6.48 μgL^{-1} for the entire lake in 2015 (almost doubled the average of 2003). 2015 was also the year values greater than 20 μgL^{-1} were first realized mainly along the shorelines as seen in the maps and graphs in substantial magnitudes.

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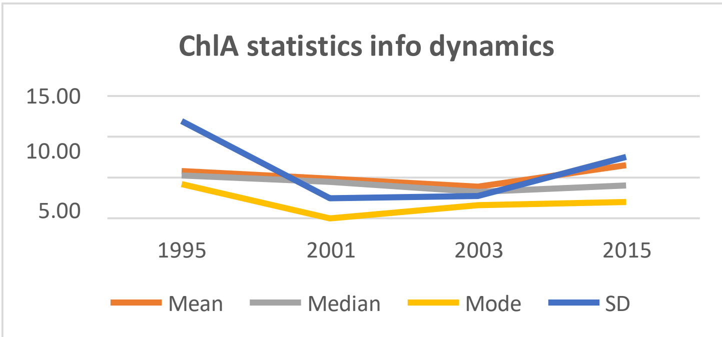

Figure 4 8: Trend lines of ChlA from 1995 to 2015

When investigated at every 4 km from the shoreline along transects, the findings showed a more emphatic pattern to the measures of central tendency for chlorophyll-a. Chlorophyll-a was reducing from 1995 to 2003 and increased thereafter. In 2015, 29 out of 38 circumstances Chlorophyll-a estimates were far greater than any ballpark figures in the previous years. Figure 4.10 elaborates this scenario Averages for observations along the transects were 7.3 µgL^{-1}, 7.77 µgL^{-1}, 5.2 µgL^{-1}, 7.15 µgL^{-1} and 18.29 µgL^{-1} for 1995, 2001, 2003, 2009 and 2015 respectively.

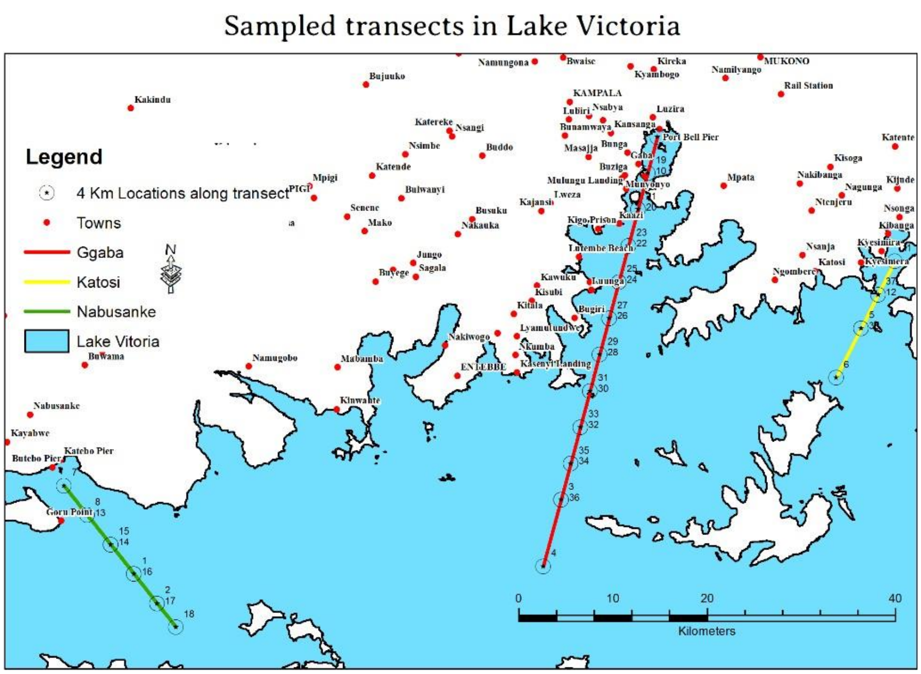

Figure 4 9: Map of transects

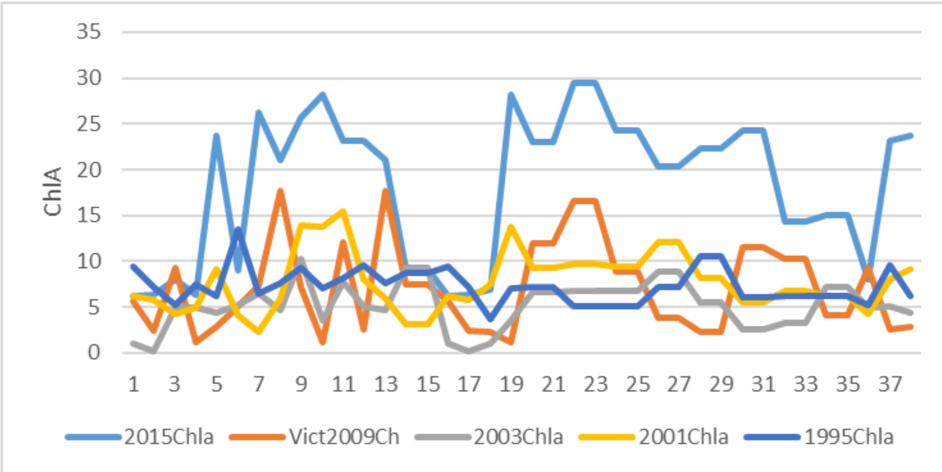

Figure 4 10: Trend in ChlA at Selected Transects from 1995 to 2015

Sentinel

Like with SDT, only images of 2017 seemed reasonably responsive to the correlational algorithm for chlorophyll-a.

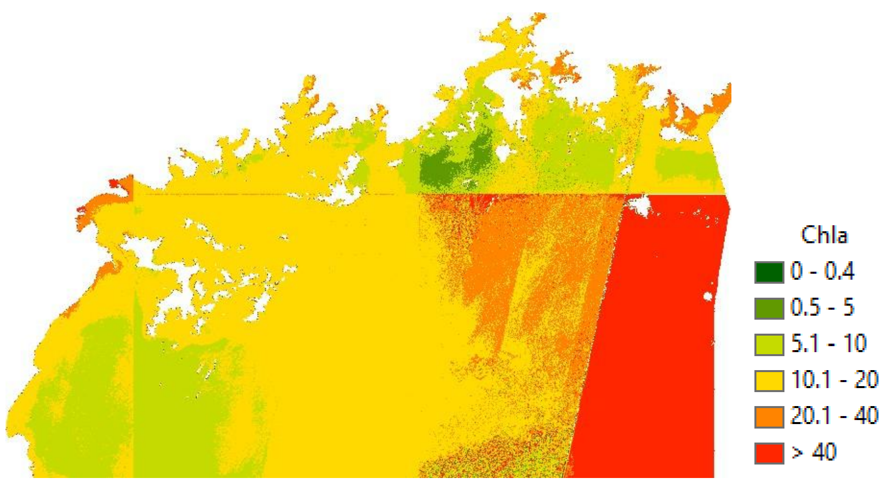

Figure 4 11 Chlorophyll-a 2017 from Sentinel 2A - 2017-01-12 &25

Sentinel images showed that by 2017, the biggest part of the lake had Chlorophyll-a above 10

μgL^{-1}. About 5% of the lake area had Chlorophyll-a less than 0.5 μgL^{-1}. Differences in acquisition dates and cloud intensities influenced values from one tile/scene to the next. The mode and median were equal to zero while the mean was astronomically higher than anticipated at 16,553.023 μgL^{-1}.

MODIS

Having ensured efforts to gather products with acquisition dates coincidental to Landsat and Sentinel 2A as well as in situ measurements, the ready to use level 2 MODIS products for Lake Victoria appeared on no occasion to cover the whole lake and in other cases had a lot of no data pixels as seen in figure 4.12.

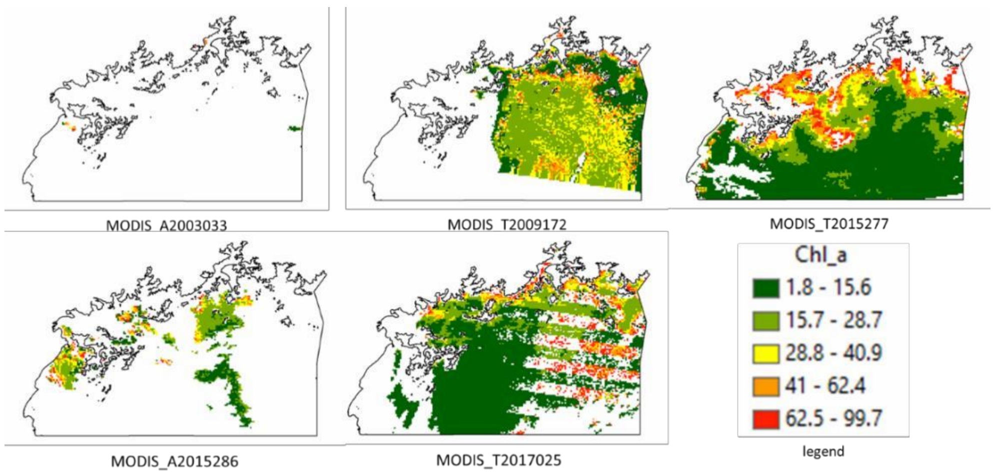

Figure 4 12 Chlorophyll-a trends from 2003 to 2017 with MODIS (aqua and terra)

MODIS was commissioned after 2001 therefore, comparison with Landsat for the years before was not possible. It is however, comforting that there is an agreement between MODIS and Landsat in 2015 registering the highest Chlorophyll-a though with differences in quantifications and dates. In Landsat, this was observed in February around day 58 yet it is observed on day 277 in MODIS of the Julian calendar. The data captured did not provide a convincing story about what was happening on the shoreline. MODIS also gave the impression that it was over estimating chlorophyll-a values perhaps due to lack of local algorithm, equation or model for correlation. The need for a local model was alluded to by Thomas *et al* (2014) while Hellweger *et al* (2004) found MODIS never to correlate to in situ measurements.

4.3Prediction from Historic Data

Because many of the predictive models required inputs at a uniform and equidistant interval whereas several others are multi–step, requiring inputs at every step, Lagrange's interpolation polynomials that do not adhere to the same were used instead. These polynomials can interpolate values for a specific set of input data points (N) having a degree of N–1 by passing a curve

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through them. Thereby constructing a continuous function based on discrete data. For Lake Victoria, there are 5 data points or (N = 5) for 31,475,791 possible locations corresponding to pixel coordinates of the Landsat images used. It is impractical generating equations for all those locations. Therefore, only three locations were chosen to simulate the likely future trends alongside the lake average for chlorophyll-a. Two of the locations were gotten from the off shore monitoring stations - UL3 and UP1 while the third was gotten from another location at 0.327N and 32.36E.

The polynomials take the form

$P(x) = \varphi 1(x)\, y1 + \varphi 2(x)\, y2 + \varphi 3(x)\, y3 + \ldots + \varphi N(x)\, yN$ equation 7

For a set of data points

$(x1, y1), (x2, y2), (x3, y3), \ldots, (xN, yN)$

Where the functions φi(x) (i = 1, 2, 3, , n) are given by

$$\varphi_i(x) = \frac{(x - x_1)(x - x_2)(x - x_3)\cdots(x - x_{i-1})(x - x_{i+1})\cdots(x - x_N)}{(x_i - x_1)(x_i - x_2)(x_i - x_3)\cdots(x_i - x_{i-1})(x_i - x_{i+1})\cdots(x_i - x_N)}$$ ....equation 8

The table 3 details the source of data points and their (x,y) while the graph in figure 4.12 shows the trends, polynomial equations and simulated future scenarios in the short and mid- term future. From the table, it is clear that there are only five data points for the three chosen locations and only 4 four data points for the mean ChlA. Since all scenarios have at least four data points, a 3rd order polynomial was taken to be ideal to investigate the likely future events.

Table 1 Data points used in future scenario simulation

ID	Sample location	1995	2001	2003	2009	2015
3	UL3	10.8104	8.98798	9.6954	6.07512	18.7399
10	UP1	3.77716	3.86489	3.17087	5.359	9.37261
32.36,0.327	other	6.643893	6.576816	2.670075	10.65959	10.07799
Entire lake	ChlA_mean	5.78	4.85	3.849		6.48

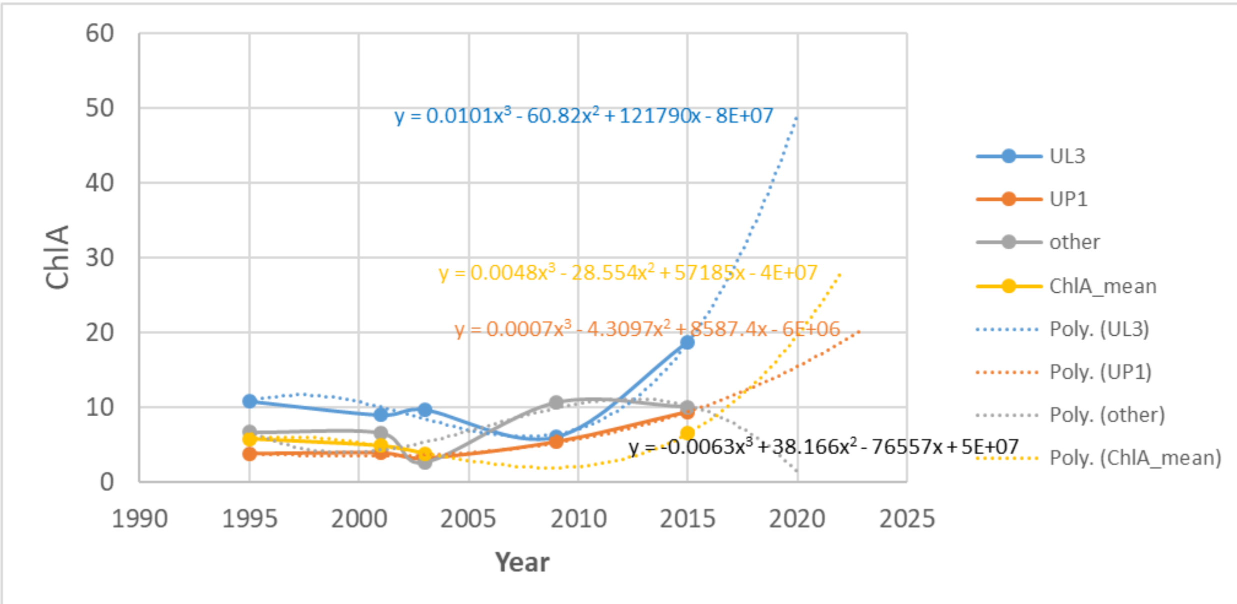

Figure 4 13 Simulation of short and mid-term future trends

After data fitting, it is evident that chlorophyll-a concentrations will continue to rise with parabolic exponential patterns nearer the shoreline than further off shore and the entire lake average. Though the entire lake concentration of chlorophyll-a will continue to rise, some spots within the lake will have their chlorophyll-a reducing. For near-shore station UL3, chlorophyll-a is expected to be almost 50 μgL^{-1} by the 2020 and way above that years after. In that very year, UP1 will be hitting the 15 μgL^{-1} mark and getting to 20 μgL^{-1} in the next three years while the mean will be rising at a slightly faster rate (20 μgL^{-1} in 2020 and almost 30 μgL^{-1} in 2023).

5.DISCUSSION

Model

Models have demonstrated that water quality parameters have been changing over the study period. SDT had been increasing or improving over the 20 year study period with an average rate of 0.07 m (7 cm) per year. Specific rates of increment for 1995-2001, 2001-2003, 2003-2009 and 2009-2015 were 0.03, 0.13, 0.04 and 0.07 meters per year respectively. Although those rates were true for the whole lake in general, different locations within the water body experienced different rates as showed by the maps and graphs with negative trends along and nearer the shoreline. The lake improvements in terms of SDT contradict earlier studies by Kayombo and Sven (2006) and Silsbe *et al* (2006) who had indicated that the SDT was declining by about a meter every decade (0.1m or 10 cm per year) on average. Nonetheless, the investigations along transects supported their arguments and as such question the statistical representativeness of the samples used in their investigations for the entire lake. Sentinel figures, though not backed up by any field measurements after 2015, affirm to the suggestion that SDT is improving as already

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appreciated with Landsat if the lake is looked at as a whole. Chlorophyll-a presented reduction rates of -0.15 μgL^{-1} per year for 1995-2001 and -0.5 μgL^{-1} per year for 2001-2003. After 2003, there was rise in chlorophyll-a concentrations with a rate of 0.22 μgL^{-1} increment per year up to 2015. Overall, there was a net reduction rate of -0.15 μgL^{-1} per year for the 20 years study interval. Still studies of specific locations are vital to reveal how such places behaved in terms of fluctuating water quality as was exemplified with the transects. Having had the greatest correlation between in situ measurements and satellite data, also being the most critical water quality parameter determining the productivity of a water body, the rate of increment of 0.22 µgL-1 per year after 2003 should be taken more seriously in determining future scenarios. This rate is expected to rise higher in the future but the rate will not be the same for different lake locations. These findings are in agreement with Ledang (n. d.) and Banura *et al* (2012) when categorizing eutrophication levels between 2003 and 2010 despite using MODIS and not giving area estimates nor rates of change. In comparison of Landsat to Sentinel, the measures of central tendency hardly related to what was observed in 2015 despite confirming to the fact that chlorophyll-a was still on the rise for the biggest portion of the lake in 2017.

Testing Validity of the Models

To eliminate bias of either sensor or year of acquisition, other Landsat datasets that did not participate in model development were used to validate the models for ChlA and SDT. These included datasets for 2003, 2007, 2013 and 2014. Since validation was to test for correctness of fit, data for the entire lake was not necessarily downloaded or used in this phase. During validation, confounding factors like effects of clouds, cloud shadows, outliers in in situ measurements and no data gaps in imagery were corrected for. This presumably explains the high regression coefficients at this stage and emphasizes the need of using great quality images as recited by Brezonik, Menken & Bauer (2005) and Leif, Bauer & Brezonik (2002).

Predicting future events

A third order Lagrange's interpolating polynomial was employed to see what is imminently likely to happen for at least three lake locations and arithmetic mean of the lake for chlorophyll-a. When the future prediction values were compared to results from Sentinel 2A for the year 2017, the mean from imagery was still inordinately higher than predicted mean (10 μgL^{-1}), LU3 (30 μgL^{-1}) and UP1 (11 μgL^{-1}). Better models for Sentinel may be required alternatively, its image processing fine-tuned some more. Because transparency showed overall improvement, possible future events were not explored. The exponentially parabolic upward trend in chlorophyll-a requires that we audit and take necessary action about the way we are managing the land use in the Lake Victoria catchment as suggested by Hellweger *et al* (2004). The way land is used outside the water body determines the extent of surface run off and hence nutrient load within the lake giving rise to extensive algal blooms, cyanobacteria as well as other disease causing agents (Zinszer, 2014). With such rise in chlorophyll-a, communities around the lake might experience similar trends in water borne diseases while realizing fewer and fewer fish catches like it has been noted by (Nakiyende *et al*, 2016).

6. CONCLUSION

In this paper we investigated the use of remote sensing as an additional means in monitoring water quality of large water bodies to determine it behaviour over time. We used Landsat series images as the principal source of sensor data. Data from both Sentinel and MODIS were also explored. Regression analysis of in situ measurements against sensor data revealed that Landsat and Sentinel were more reliable in water quality studies. Our contribution in this paper is derivation of local algorithmic models that can be used to investigate water quality on Lake Victoria using Landsat and Sentinel images. A local algorithm for MODIS for use in water quality studies was emphasized as a gap. And like in many remote sensing studies, clouds remain the number one challenge of using optical data aboard space platforms.

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