EXPLORING MODIS IMAGERY IN MONITORING WATER QUALITY ON LAKE VICTORIA

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ABSTRACT

At 68,800 km^2, Lake Victoria is the largest fresh water lake in Africa. It is a trans-boundary water resource supporting the livelihoods of over 20 million people directly and indirectly. It is a source of food, recreation, domestic and industry use. This has rendered its monitoring of paramount interest to several environmental agencies in Uganda, Kenya and Tanzania as well as along the river Nile basin. Traditionally, the monitoring of water quality is carried out at specific points of the lake by carrying out in-situ measurements or collection of water samples for laboratory testing. This traditional approach of determining water quality is cumbersome, expensive and does not give a synoptic perspective of the whole lake. This has inspired the consideration of satellite imagery as a tool to monitor water quality on the lake. Satellite imagery offers the advantage of providing regularly collected data, giving a synoptic view of the water quality of the whole lake. The aim of this paper was to therefore investigate how satellite derived water quality parameters compare with in situ measurements in a bid to operationalise the use of satellite images in monitoring water quality on the lake. To wit, in-situ lake surface temperature at specific points was measured and water samples of those points were taken to the lab to test for Chlorophyll_a. These samples were collected within 4 hours of satellite overpass. These results were then compared with water quality parameters derived from MODIS imagery. The results showed that there is a moderate to strong correlation (R^2 = 0.68) between satellite derived lake surface temperature and in-situ measurements implying that MODIS satellite imagery can be depended to accurately model the spatial variation of lake surface temperature. Unfortunately because of cloud cover coinciding with the day of in-situ observations, no similar comparisons could be made regarding Chlorophyll_a, thus portraying one of the challenges of operationalizing the use of satellite imagery in monitoring water quality on lake Victoria. Given the potential of satellite imagery as a reliable source of water quality information, further studies are urgently needed to validate it for Lake Victoria.

INTRODUCTION

Remote sensing of inland lakes has in the recent past gained currency and increasingly studies are being undertaken to use satellite imagery operationally (Zhu et al. 2004). This is mainly motivated by the fact that in-situ measurements are costly, do not give a synoptic perspective of the lake, are irregularly done and are cumbersome (Watkins, 2009). Satellites on the other hand regularly orbit the globe collecting information about the earth's surface. This information is usually archived and in many instances is freely available, thus enabling historical studies of a lake's characteristics. Current research is increasingly focussing on how to best relate imagery radiances to water geophysical parameters (Teillet, 1997). Whereas the use of satellite imagery to monitor water quality parameters on oceans has reached maturity, its adoption for inland lakes is mainly experimental due to the high degree of optical complexity of inland waters (Zhu et al, 2004). Some of the water quality parameters that have been monitored using satellite imagery include Chlorophyl_a, lake surface temperature, water transparency, dissolved organic matter etc (Fengyun, 2010).

The interest in Chlorophyll_a stems from the fact that it is contained in all species of phytoplankton (Thiemann and Kaufmann, 2000) and is indicative of the level of eutrophication of the lake (Koponen et al., 2001). Lake Surface Temperature (LST) is important for bulk hydrodynamic and ecological variables (Watkins, 2009). It also is used to mark surface water temperature fronts (Ullman et al., 1998) and to develop upwelling indices (Platnner et al, 2006) which is of particular interest to the fisheries industry. Lake Surface Temperature is also important because it gives an indication of a lake's biological and chemical activity (MacCallum and Merchant, 2012; Stefouli and Charou, 2012).

This paper focuses on attempts by the authors to explore and validate the use of satellite imagery in monitoring water quality on lake Victoria using the Moderate-resolution Imaging Spectroradiometer (MODIS) Imagery, with particular focus on the Murchison Bay in Kampala, Uganda. The choice of MODIS Imagery is motivated by the fact that it has a daily temporal resolution, synoptically covers the whole lake at a go, and is freely available online. Lake Victoria is the largest lake in Africa covering an expanse of 68,800 km^2 (Carvalli, et al., 2009). By its size, any water quality monitoring strategy is challenging due to costs involved. This is further complicated by the fact that Lake Victoria is trans-boundary, surrounded by Uganda, Kenya and Tanzania. All these factors build the case for the need of satellite imagery in developing an operational strategy of monitoring water quality for the lake. This paper therefore discusses the challenges in using and validating satellite derived water quality parameters for Lake Victoria.

METHODOLOGY

The main thrust of the research was to validate satellite derived water quality parameters with traditionally determined water quality parameters. The water quality parameters considered were Lake Surface Temperate (LST) and Chlorophyll_a. Endeavours were made to collect the water samples within three - four hours of the MODIS overpass. Satellite overpass was predicted using the NASA's Ocean Color website (http://oceandata.sci.gsfc.nasa.gov/cgi/overpass_pred). In the case of Lake Victoria, MODIS (aqua) traverses at about 11 am. At each sampling point, location was determined using a handheld GPS while LST was measured using a thermometer to measure the 'skin' surface temperature (i.e. top surface of the lake) as this is the temperature that the sensor detects (Robinson, 2010). At each of these locations, water samples were collected and stored in cool boxes for further testing and analysis of Chlorophyll_a concentrations in the laboratory. There being no guide as to how to sample the locations, points were randomly selected at about 1 km apart within the Murchison Bay. Figure 1 depicts the sampling points in Murchison Bay of Lake Victoria in Uganda

Figure 1: Study area (Courtesy of Google maps – Copyright: Map Data 2014 Google)

MODIS imagery of Lake Victoria for the days that samples were taken was retrieved from NASA's ocean color web site (http://oceandata.sci.gsfc.nasa.gov). 'Level 2' data has been processed by NASA from raw spectroradiometer data to estimate surface water temperature and Chlorophyll_a. LST was extracted from the imagery by using MODIS bands 31 and 32 at 11µm and 12µm. The algorithm for computing LST from observed brightness temperatures is shown in equations 1 - 5 (Franz, 2006):

For dBT<= 0.5

$$LST = a00 + a01*BT11 + a02*dBT*bLST + a03*dBT*\left(\frac{1}{Cos(\phi)-1}\right) \quad (1)$$

For dBT>= 0.9

$$LST = a10 + a11*BT11 + a12*dBT*bLST + a13*dBT*\left(\frac{1}{Cos(\phi)-1}\right) \quad (2)$$

For 0.5 <dBt< 0.9

$$LST(lo) = a00 + a01*BT11 + a02*dBT*bLST+ a03*dBT*\left(\frac{1}{Cos(\phi)-1}\right) \quad (3)$$

$$LST(hi) = a10 + a11*BT11 + a12*dBT*bLST + a13*dBT*(\frac{1}{Cos(\emptyset)-1}) \quad (4)$$

$$LST = LST(lo) + \frac{dBT-0.5}{(0.9-0.5)*(LST(hi)-LST(lo))} \quad (5)$$

Where:

BT11 = Brightness temperature at 11 µm, in deg-C (i.e. band 31)

BT12 = Brightness temperature at 12 µm, in deg-C (i.e. band 32)

dBT = BT11 - BT12

LST (lo)= Lake Surfac Temperature when dBT>= 0.5

LST (hi) = High Lake Surface Temperature when dBT>= 0.9

bLST = Baseline Lake Surface Temperature

Cos(ø) = Cosine of sensor zenith angle

The coefficients a00, a01, a02, and a03 and a10, a11, a12, and a13 are based on match-ups between the satellite retrievals of brightness temperature and field measurements of sea surface temperature.

Chlorophyll_a was extracted from the imagery using the Ocean Colour algorithm version 5 (OC3v5) (O'reily et al. 2000). The algorithm form describes the polynomial best fit that relates the log-transformed geophysical (in this case Chl-a) variable to a log-transformed ratio of remote-sensing reflectances (of the MODIS imagery):

$$Log10(Chla)=0.241-2.477r+1.530r2+0.106r3-1.108r4 \quad (6)$$

where

r = Log10 {(Rrs 443>Rrs490)/Rrs555}

Rrs – electromagnetic wavelengths used for Chl-a extraction

The input radiances are in the form of either remote sensing reflectance or normalized water leaving radiance.

WIMSOFT software was used to extract the satellite derived water quality parameters in order to facilitate comparisons with the in-situ measurements. To extract the LST and Chl_a concentration at a given location of interest from the MODIS imagery, the 3 x 3 pixel mean is calculated of a 1 x 1 km pixel. The Pearson product-moment correlation coefficient was then used to determine the degree of correlation between satellite derived and in situ water quality parameters using a 5% ($p \leq 0.05$) level of significance.

RESULTS AND DISCUSSION

The table 1 shows the days when samples were collected and the corresponding status of imagery

Table 1: Sampling expedition vis a vis status of imagery

Date of expedition	**Status of Imagery**
1st June 2013	Imagery available, however cloud cover made it impossible to obtain satellite derived Chlorophyll_a, though some LST was determined
15th June 2013	Study area overcast hence no corresponding satellite derived water quality parameters
31st January 2014	Imagery available, however cloud cover made it impossible to obtain satellite derived Chlorophyll_a, though some LST was determined
7th June 2014	No imagery for the study area

Unfortunately none of the sampled points Chl_a could be compared with satellite derived Chl_a because of cloud cover on the days of sampling. Lake Victoria is located along the equator and is notoriously bedevilled by cloud cover. Since MODIS uses the optical bands to derive Chl_a, it poses a big hindrance in its extraction. This evidently presents a challenge in the adoption of satellite imagery in monitoring quality, as all samples collected during cloud covered days could not be correlated with satellite derived water quality parameters. The second reason why the study may have yielded no results could have been based on the fact that the sampling points were close to the shore. The choice of Murchison bay as a case study in this research was motivated by, among other reasons, that it is the main abstraction point for the National Water and Sewerage Corporation (NWSC), thus rendering NWSC a potential beneficiary of this study as they depend on regular water quality information for their operations. These abstraction points are less than 1 km from the shores, and unfortunately water quality information collected here could not be used to validate satellite derived water quality information because of the so called 'adjacency effect'. In other studies such as (Watkins, 2009) it is suggested that for better assessment of Chlorophyll_a, more reliable results could be obtained by separating sampling between nearshore (< 30m depth) and offshore (> 30m). Figure 2 depicts an annual satellite derived Chlorophyll_a for Lake Victoria for 2003 and as can be seen the areas closer to the shore often times don't have any Chl_a values, probably indicating that whereas MODIS can be effective in depicting synoptic Chl_a distribution, it seems handicapped in determining Chl_a distribution in bays which define the lake shore's outline. The downside of this is that it is in the bays that there is most pollution, it is where water abstraction occurs and there is need to continually monitor these areas. Future expeditions will have to be made further into the lake if validation of satellite derived chl_a is to be successfully validated for Lake Victoria.

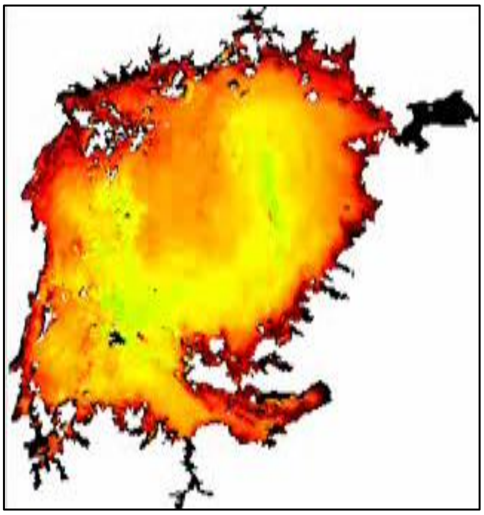

Figure 2: 2003 Annual Satellite derived Chlorophyll_a distribution

To determine LST, only two images could be used of which only 14 out of 30 sampled locations could be correlated with satellite derived LST. The figure 3 show cases the relationship between in-situ and satellite derived LST. The Pearson Correlation Coefficient for the Satellite derived vis a vis the in-situ LST gives $R^2 = 0.68$ which is significant at the $p = 0.05$ level. This depicts moderate to strong positive correlation, indicating that there is a tendency for satellite derived LST to vary positively with in-situ LST measurements. Similar studies on other lakes have presented higher R^2 Pearson Correlation Coefficients. This research could be further improved by using a bigger sample size.

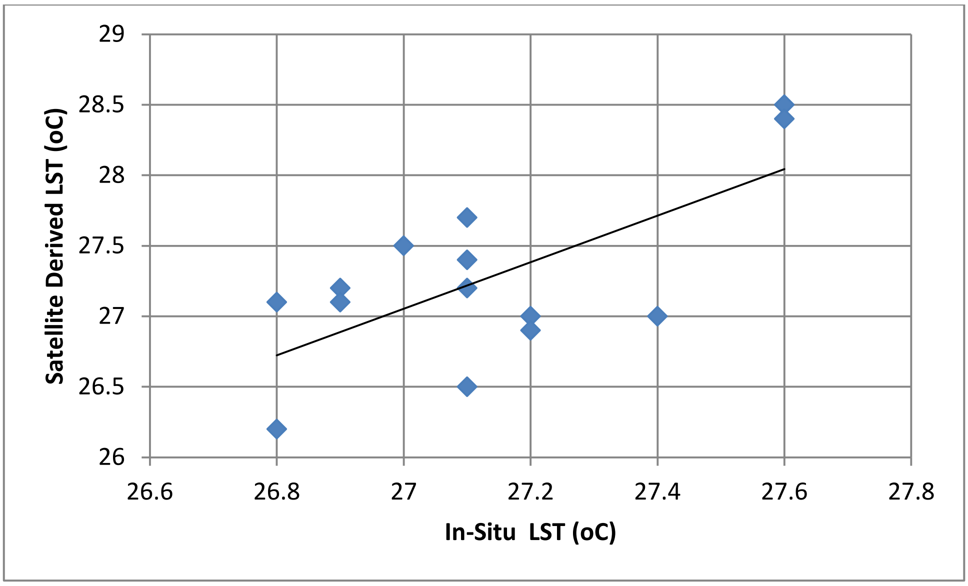

Figure 3: Comparison of satellite derived LST with in-Situ measured LST

CONCLUSIONS

From this research, it is evident that there is need to further explore the applicability of satellite imagery in monitoring water quality on lake Victoria. For this occur, a bigger sample will be required, with samples preferably collected at least 1 km from the shores. Secondly, the influence of cloud cover is not trivial, nonetheless there is need to explore means by which this challenge can be circumvented. To increase on the possibility of collecting samples on cloud free dates, precipitation/cloud prediction models may have to be considered to increase the possibility of collecting verifiable satellite derived water quality data. The strong moderate to strong correlation between satellite derived and in situ LST demonstrates that satellite imagery can be relied upon to determine spatial variation of LST on the lake. This will be further ascertained when more data is collected.

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