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Using Satellite Remote Sensing Data in Monitoring Water Quality at Ndakaini Reservoir Dam, Kenya

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ABSTRACT

Pollution from anthropogenic and natural processes threatens most fresh water resources. In Kenya, drought and occasional floods affects water quality negatively impacting health of humans and ecosystem. Currently the use of in situ observation methods for monitoring water quality is inadequate, periodic and at selected sample points. The potential of remote sensing-based techniques in examining water quality in open water bodies is explored. Aim of this study was to assess variability in Chlorophyll concentration (Chl_a), water temperature (SST) and Suspended Sediment Concentrations (SSC) of Ndakaini Dam before and after the destructive April-May 2018 floods. Landsat 8 OLI imagery and QGIS V 2.14 Essen geospatial software were used. The results indicated that Chlorophyll concentration levels decreased by 0.26mg/l, water temperature dropped by 3^0C while Suspended Sediment increased by 2.57mg/l. Generally, analysed water quality parameters showed a spatial and temporal variation across the April-May 2018 floods. Ndakaini dam was found to be a low-level pollution mesotrophic reservoir.

Keywords: Ndakaini Reservoir, Remote sensing, Water Quality, real-time monitoring, Pollution

INTRODUCTION

Fresh inland water bodies are important for recreational, economic and ecological use. Globally, demand for fresh water has escalated leading to excessive abstraction. On the other hand, the ever-growing water demand has increasingly fueled local water crises. On the same note the quality and quantity of fresh water resources has declined owing to population growth, migration, industrialisation and urbanization (Tessema et al., 2014; Torbick et al., 2013; WWAP, 2015). Today, threats of pollution, land use and climate change pause serious challenges as far as water conservation and management is concerned. Unregulated human activities have affected water bodies resulting to seasonal water scarcity, increase in nutrients and sediment loadings (Mushtaq & Pandey, 2014).

Surface waters are amongst the most polluted water resource from industrial, domestic and municipal sources (Corcoran et al., 2010). Water for human consumption require high standards of quality and therefore monitoring provides key information for detecting contaminants and assessing the suitability of available water resources for human use (UNEP,2010; WMO,2012).

Major challenge on effective monitoring of water quality is due to lack of adequate, consistent and update information (UNEP, 2010). Traditional insitu methods of measuring water quality tend to give accurate but discrete measurements at selected sample points and do not cover a large water body (Abdelmalik, 2018; He et al. 2008).

Use of satellite remote sensing data in water quality assessment hold significant potential as demonstrated by Mathews,2011; Schaeffer et al., 2013; Saadi et al, 2014. In particular, Landsat data products have been widely used for assessment of inland lakes water clarity and chlorophyll concentrations. Landsat's data availability, moderate spatial resolution and reduced temporal coverage makes it widely used (Steven et al, 2002) In Kenya, although many studies have been done on assessment of selected Water quality variables at varying spatial

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levels (Gathenya et al, 2009; Mueni, 2014) the application of satellite data has not received much attention especially in the field of water quality assessment (Song et al,2011; Chawla et al, 2020)

There is need to explore the potential of satellite based observation in predicting water quality on domestic water use dams in Kenya. Overall objective of this research was to assess chlorophyll concentration, water temperature and turbidity at Ndakaini dam before and after the April-May 2018 floods using Landsat 8 Operational Land Imager sensor data.

Study area

Ndakaini dam is one of the two reservoirs supplying water to Nairobi City County. This dam supplies over 84% of water to the residents of Nairobi County. The dam is located between latitudes 00^0 48' & 00^0 49’South and Longitudes 36^0 49, & 36^0 51’East on an altitude of about 2,041 Meters above sea level (figure.1) The dam land covers 1200 acres and it has a catchment area of 75sqkm. Ndakaini dam has a storage capacity of 70 million cubic meters occupying 600 acres when full. The area has well drained, deep, dark reddish brown, friable clay soil (Saytarkon, 2015). Ndakaini Sub location where Thika dam (Ndakaini dam) is found has a population of 2444 persons (KNBS, 2009) and covers area of 8.5sqKm. On average the area receives 2000 to 2500 mm of rainfall per annum.

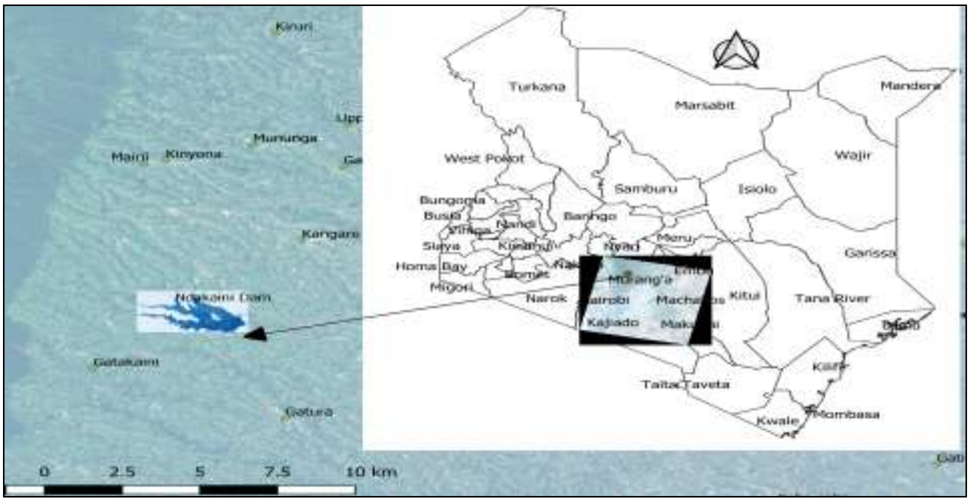

Figure.1: Location of Ndakaini Dam on South Eastern slopes of Abardares ranges (Source: Author)

MATERIALS AND METHODS

Materials

Software

ACOLITE version 3.2 software was used for radiometric calibration of Landsat 8 OLI sensor to generate spectral radiance and reflectance values. In particular, ACOLITE was used to decode Landsat MTL text file and build an expression to create a radiance image from the raw pixel digital numbers. SEADAS was used to visualise derived land to water Output parameters. QGIS version 2.14 was used in delineating region of interest and to raster clip the area of study from the two multi-temporal images.

Satellite images

Landsat 8 OLI datasets of 29th January 2018 and 12th October 2018 were used. Level 1 Landsat 8 OLI data was downloaded from USGS Earth Explorer and later converted to tiff for input into image processing software. Landsat 8 OLI has a temporal resolution of 16 days with spatial resolution of 15m for Panchromatic, 30m for visible band and 100m for thermal band (USGS, 2016). In this study band 1, band 2, band 3, band 4 and band 10 respectively of Landsat 8 OLI sensor were used (table.1). Images downloaded were those with minimal cloud cover since clouds obstruct data returning “No data” value from the ground features.

Table1. Landsat 8OLI Bands specifications as used in water quality monitoring

Band	Path/ Row	Date of Acquisition	Band wavelength
1	168/ 61	29-01-2018/ 12-10-2018	433nm - 453nm
2	168/61	29-01-2018/ 12-10-2018	450nm - 515nm
3	168/61	29-01-2018/ 12-10-2018	525nm - 600nm
4	168/61	29-01-2018 / 12-10-2018	630nm – 680nm
10	168/61	29-01-2018/ 12-10-2018	10300nm – 11300nm

METHODS

Landsat Data Acquisition

Landsat 8 OLI images of path 168, Row 61 were downloaded from USGS Earthexplorer website (http//www.usgsearthexplorer). Landsat images used in this study were those with cloud cover of less than 10%. Images of 29th January 2018 and 12th October 2018 had cloud cover less than 8% and were selected to represent "before" and "after" the April-May 2018 floods scenario.

Image pre-processing

First, radiometric correction was done on spectral bands 1, 4 and 10 by converting the digital numbers to spectral radiance signals. This was realised by using a Chander & Markham, 2003 expression; $L\lambda=[(LMAX\lambda-LMIN\lambda) / (QCALMAX)] * QCAL + LMIN\lambda]$

In order to retrieve water surface reflectance values, atmospheric correction was done on the resultant image. Then, resultant spectral radiance was converted to top of atmosphere reflectance using equations 1 and 2 obtained from USGS website (http://landsat.usgs.gov);

$\rho\lambda' = M\rho * Qcal + A\rho$; Equation (1)

Thereafter, the top of atmosphere reflectance was corrected using sun angle correction equation as shown;

$\rho\lambda = \rho\lambda' / \cos(\theta sz * \pi/180) = \rho\lambda' / \sin(\theta se * \pi/180)$; *Equation* (2)

3.2.3 Mapping Chlorophyll Concentration Levels

To map levels of chlorophyll_a concentrations across the dam, normalised digital water index (NDWI) algorithm expression by Zhang & Hang, 2015 was used.

$$Chl\_a = 17.878*(OLI\ 4 - OLI\ 1/\ OLI4 + OLI\ 1) + 5.636$$

Where; OLI 4 is red band, OLI 1 is coastal / aerosol band of land sat 8 Operational Land Imager (OLI) sensors.

Calculating Water Surface Temperature variations

Temperature influence amount of oxygen dissolution in water. Thermal Infrared (TIRS) band 10 of land sat 8 OLI was used. Thermal Infrared raw digital numbers were converted into the top of atmosphere spectral radiance using the radiance expression in Landsat Tools V1.0.34;

$L\lambda = (0.0003342 * Qcal\_B10) + 0.1$

To generate temperature map, top of atmosphere spectral radiance was converted into brightness temperature using thermal constants provided in the metadata file;

Temp= 1321.0789 / (Ln (774.8853 / Rad_B10) + 1)

Created temperature maps were converted into degrees Celsius by subtracting a value 273.15 from the resultant maps

3.2.5 Mapping Suspended Sediments

To map spatial and temporal variation in the concentrations of suspended sediments polynomial model by Kumar, (2016) was applied to calculate the amount of suspended particles from remote sensing data;

SS= 13181* OLI 4^2 -1408.6 * OLI 4 + 44.15

Tropical State Index (TSI) estimation for Ndakaini inland Reservoir Lake

To understand the quantity of algal biomass content in Ndakaini dam, tropical state index was used. Carlson developed an expression to map trophic state of lakes based on Secchi disk transparency, chlorophyll_a concentration or total phosphorus content (Carlson,1977). For this research chlorophyll_a was used to calculate the tropical state index using a formula by Pulak et al, 2016

Tropic State Index Chlorophyll =10 [6-(2.04-0.68ln(chl-a))/ Ln2]

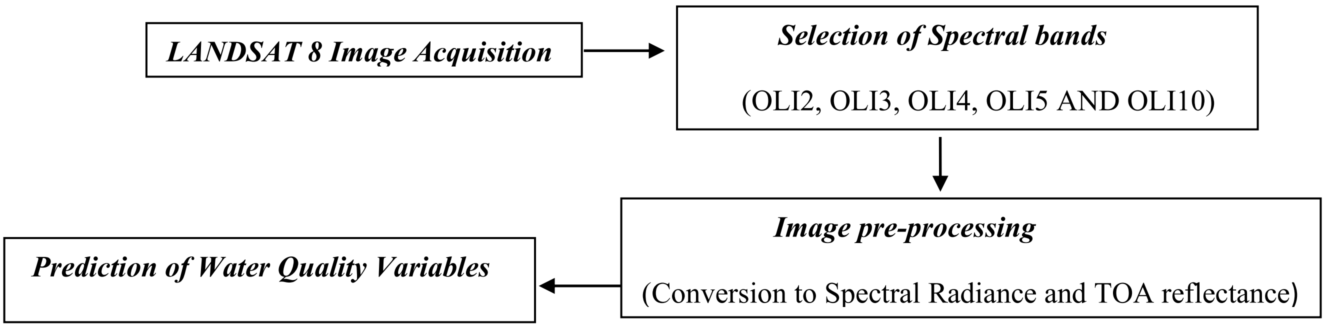

Figure 2: Simplified flow chart of the water quality variables retrieval methodology

RESULTS AND FINDINGS

Spatial-temporal variation in Chlorophyll_a levels

Chlorophyll_a concentration levels within Ndakaini dam on 29th January 2018 were found to be in the range between 5.87 Mg/l to 20.9 Mg/L with an average concentration of 10.42 Mg/L and a shown a standard deviation of 5.25 Mg/L (fig.3). January was selected as the “dry “month image before the floods. Usually during this month, increased evapotranspiration due low precipitation leads to reduced water quantity in the reservoir which in turn lead to raised concentration of the chlorophyll-a.

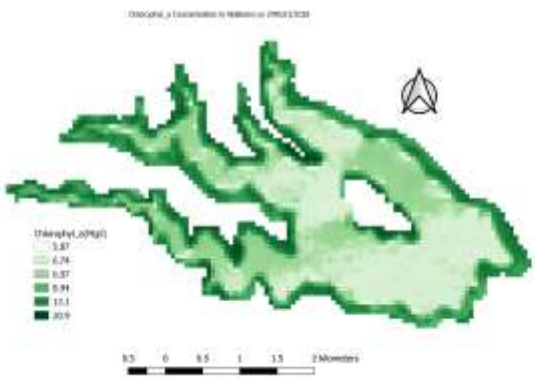

Figure.3: Map of Chloropyhl_a Levels on 29th /01/2018

Chlorophyll_a concentration levels in the reservoir on 12th October 2018 were lower compared to those mapped on January (10.42 Mg/l to 10.16 Mg/l). The concentrations of chlorophyll_a varied from 7.94 Mg/L to 15.60 Mg/L and mean concentration of 10.16 Mg/L with standard deviation of 2.51 Mg/L as shown in figure 4. As the rain season set in, increased overland flow into the reservoir from streams result to volumetric capacity increasing which reduces the concentration of the chlorophyll-a within the dam.

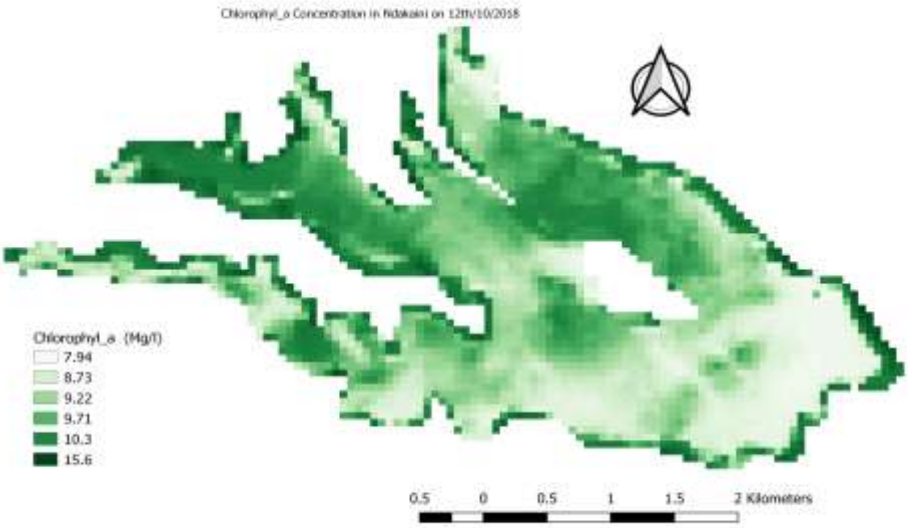

Figure.4: Map of Chloropyhl_a Levels on 12th /10/2018

Dam's Open Water Surface Temperature Dynamics

The dam's open water surface temperature as calculated and ultimately map on 29th January 2018 ranged between 21.7^{0}C to 32.3^{0}C with mean temperature of 27.0^{0}C (Fig.5). These were higher compared to those calculated for the month of October 2018. During this month the water levels were low and as such the open water heating from the surface transfer a lot of direct heat into the reservoir bottom which raise the water temperature conventionally.

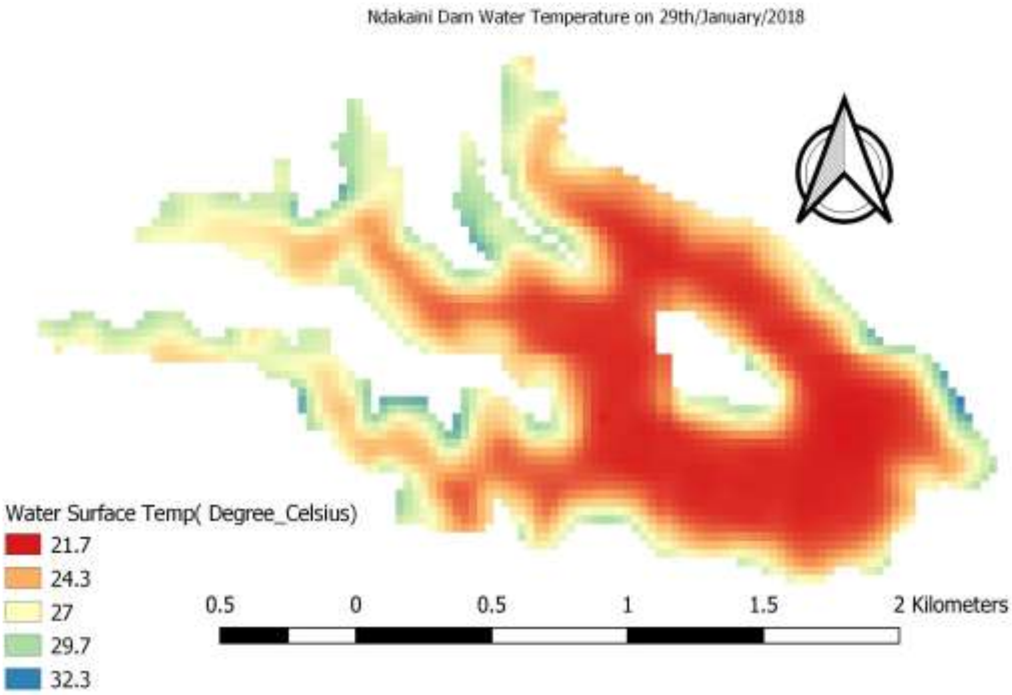

Figure.5: Map of Water temperature for Ndakaini Dam on 29th/01/2018

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October showed lower water surface temperatures being after the April-May 2018 long rains. The mapped temperature ranged from 19.9^0C to 28.03^0C. The month's average temperature was 24.0^0C. This was attributed to the increased reservoir water levels from stream inputs draining into dam (Fig.6). After the floods, the water levels in the dam increased which led to even distribution of water heat by currents translating to lowering of the open surface water temperature.

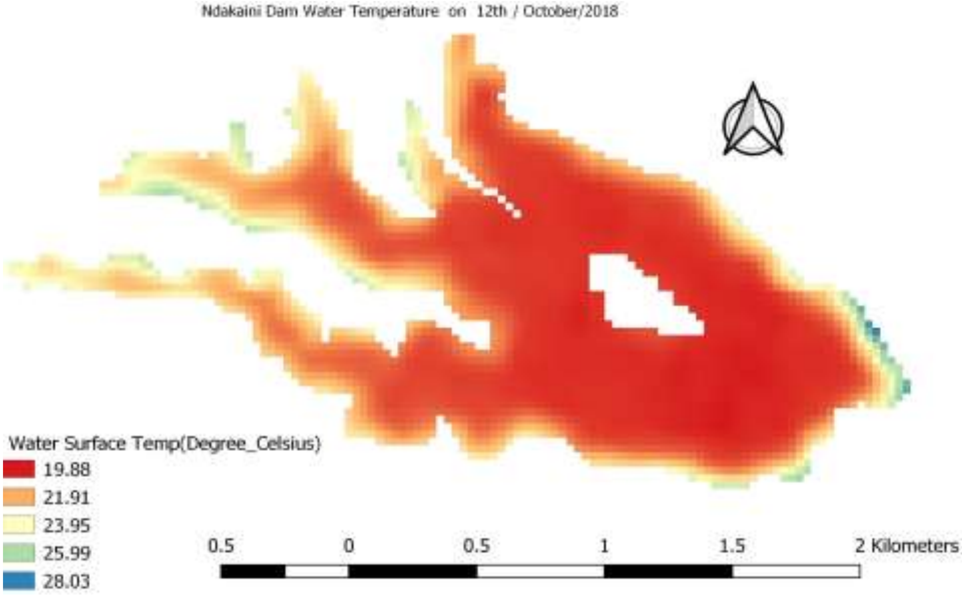
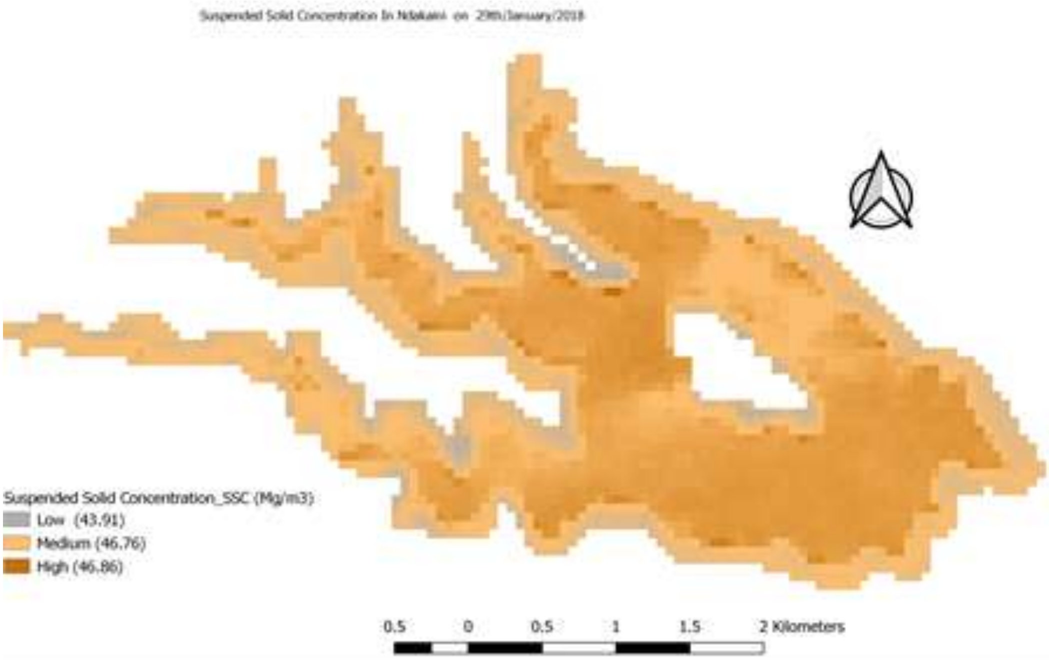


Figure.6: Map showing Water temperature for Ndakaini Reservoir on 12th /10/2018

Suspended Sediments Concentration variations

Suspended Sediment loadings across the entire dam were map during the months of January and October. Average amount of suspended sediment concentrations as calculated from Landsat 8 OLI bands on 29th January and 12th October ranged between 45.84 Mg/L in January to 48.41 Mg/L on October 2018 (Fig.7). The increase of 2.57 Mg/L sediment concentration between January and October was linked to surface run-offs and increase stream input. The observed variation is associated with sediment load distribution within the reservoir by inflowing stream discharge which brought more sediment in as much as it aided in the spreading it within the reservoir.



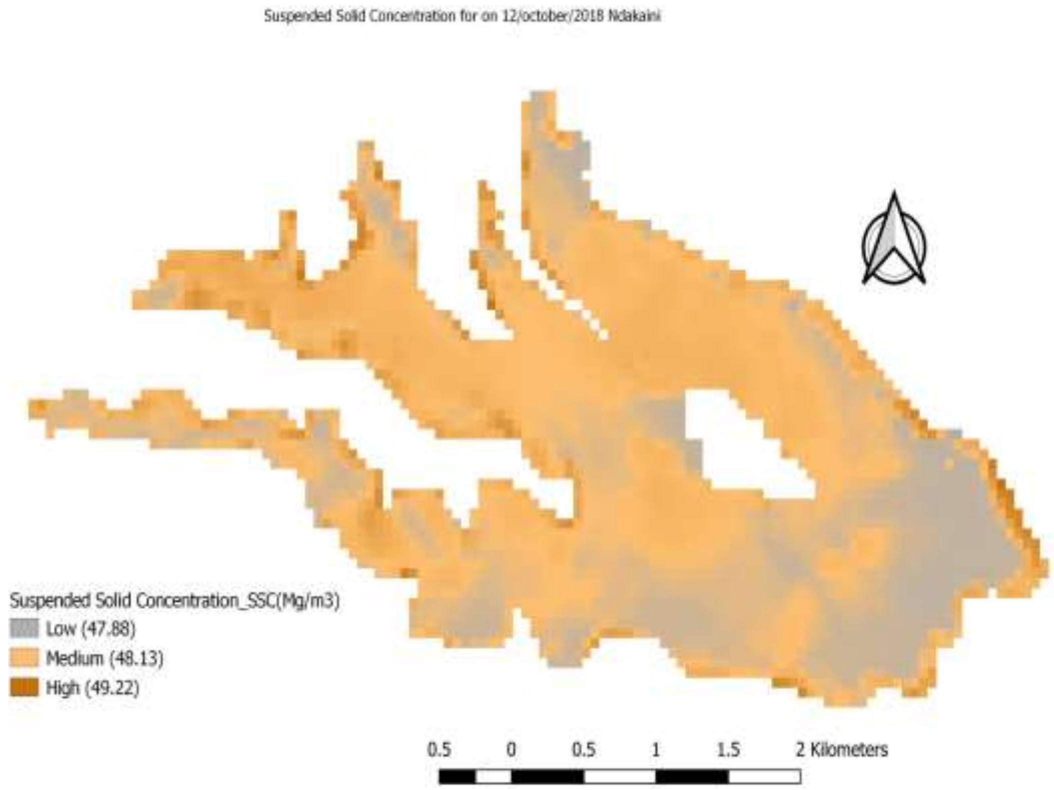


Figure.7: Map of Suspended Sediment Loads on 29th /01 2018 and 12th /10/2018

DISCUSSION AND CONCLUSION

The observed spatial and temporal variation in chlorophyll a concentration, surface water temperature and suspended solid components during and after the April 2018 floods was attributed to dynamics in dam nutrient inputs and water volume. The tropic state index value of this lake indicates Ndakaini dam is mesotrophic lake water with low level of pollution. The lake's capacity varies from 457.02 acres before the floods (low water volume) to 574.89 acres after the flood (High water volume) as shown in figure 8 below. This also explains the observed low Chlorophyll a concentration in October compared to January due to increased water input.

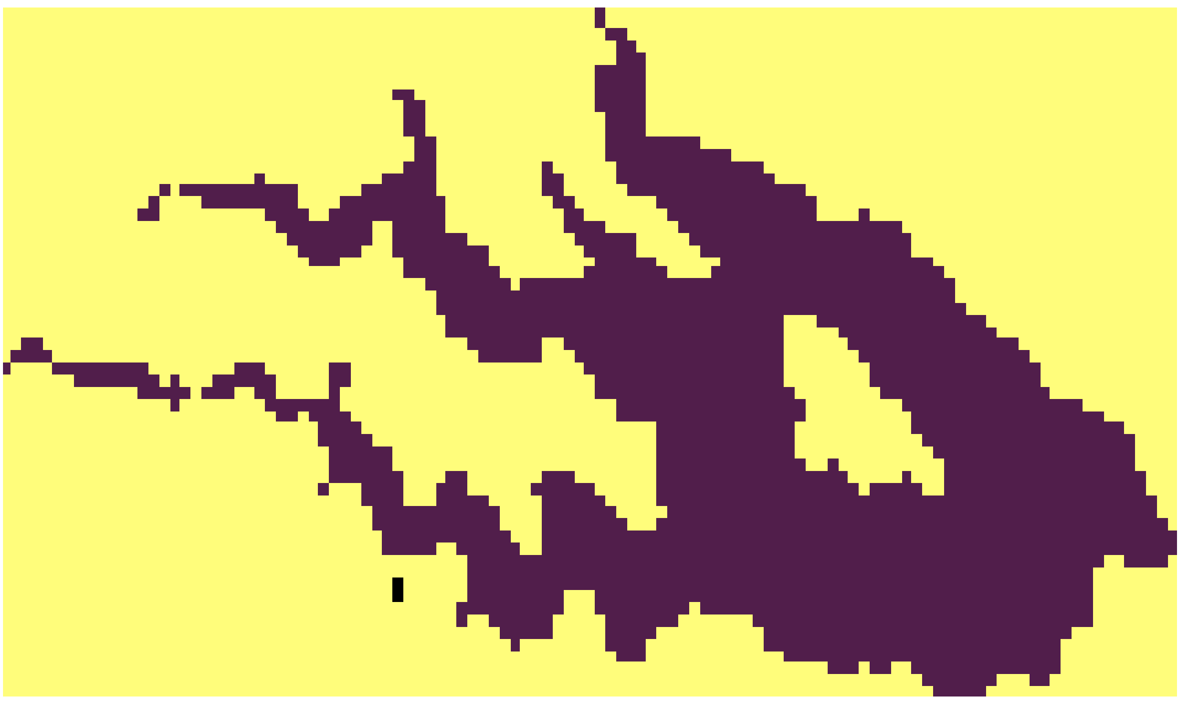


Figure. 8: (A) Before the flood's lake extent (457.02Acres)

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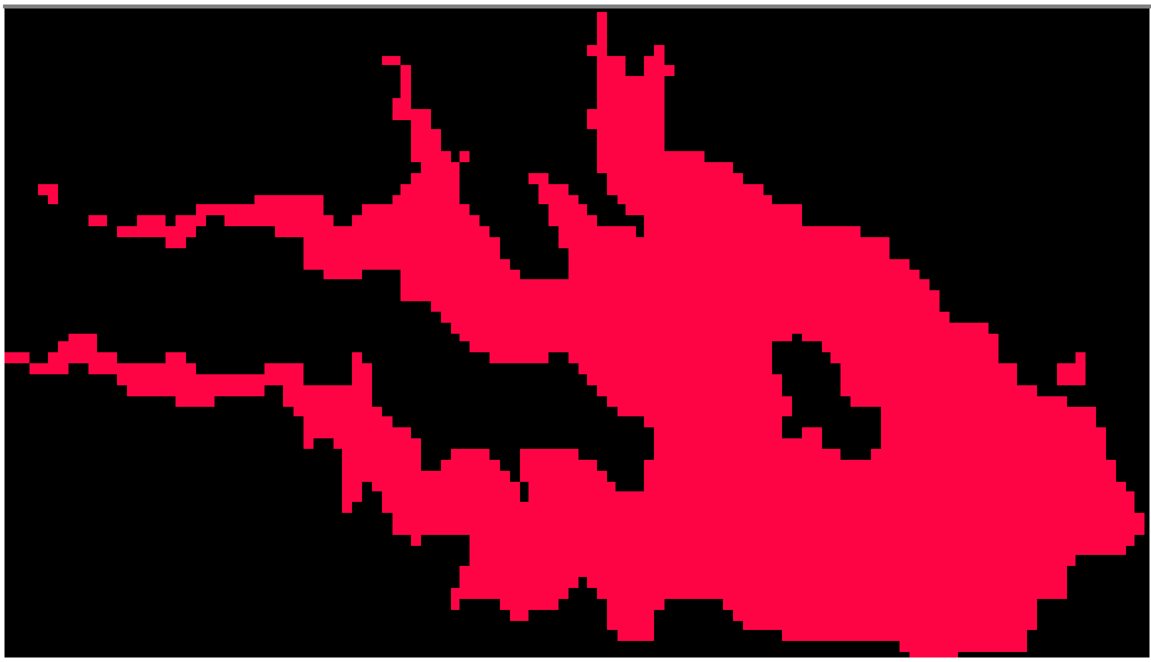

Figure.8: (B) After the flood's lake extent (574.89Acres)

This study advocates the use of remote sensing data for long-term monitoring of water quality conditions as well as in predicting water quality variables for open surface water bodies which are inaccessible. Furthermore, there is a need to integrate Geospatial tools with insitu measurements to strengthen the current water monitoring and assessment methods if Kenya's surface water resources are to help achieve the Vision 2030 and SDG no.6.

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