About:

**1. Spatio-temporal Remote Sensing, automated *in-situ* IoTsensors & ML to monitor and predict HABs and cyanotoxins.**

Case Study-Lake Victoria

**2. Intro**

Algae, in limited concentration, are ecologically friendly however when an unanticipated bloom comes to pass, can have severe impacts on human health, aquatic ecosystems, form unsightly views and nuisance in points of impact and with cyanotoxins, initiated by the cyanobacteria being particularly problematic as they can be toxic and scum-forming, posing a risk to the ecosystem and to public health and as well detrimental to the economy.

The geoscientific preparedness to monitor and predict algal and cyanobacteria blooms of great material value to provide pre-warning to society and enable management processes to be activated in advance to limit the disastrous and catastrophic impact.

Previous work

Satellite data from the Sentinel 2 platform can be successfully used for estimating algal concentrations in lakes.

The advent and uptake of high resolution in-lake automated water quality sensing technology together with new satellite platforms now enables a step-change in data availability that could be used for monitoring and forecasting of cyanobacteria (and algal) blooms in Lake Victoria.

Here I intend to utilize Earth Observation data, including from new satellite platforms, new in-situ sensor technology, available meteorological data, combined with machine learning techniques to provide a near real-time, intelligent capacity for assessing current state and providing short-term forecasts of likelihood of algal and cyanobacteria blooms in Lake Victoria.

**3.Motivation and Problem Statement**

With the growth of industries along the Lake Victoria regions, there has been reported enrichment of nutrients, increasing the amount of plant and algae growth in the Lake. Lake Victoria has been reported to face eutrophication challenges, resulting in an increase of bloom-forming cyanobacteria (CynoHABs), (Martin K., et al. 2019).

*Many cyanobacteria species can produce toxins that affect the nerve system, liver, and skin and cause harmful impacts on humans and their companion animals e.g pets using them for drinking water or recreation. HABs can also damage freshwater ecosystems, such as polluting beaches, causing taste and odor problems for drinking waters, lowering the ambient light required for submerged aquatic vegetation, and depleting oxygen levels and hence killing fishes [8]. HABs have become one of Remote Sens. 2020, 12, 3278; doi:10.3390/rs12203278 www.mdpi.com/journal/remotesensingRemote Sens. 2020, 12, 3278 2 of 18 the major water quality issues for inland waters in some states [9]. The cost of water treatment has been an economic burden in recent decades [1]. Despite the significant negative impacts of HABs on ecosystems, the economy, and public health, they are not monitored and assessed on a regular basis due to the high cost and the sparsity of ground water quality sampling data [1]. Remote sensing has been increasingly used for monitoring and mapping HABs in aquatic systems, as it is capable of collecting synoptic data over multiple spatial and temporal scales [10–19]. It has been demonstrated that satellite and airborne optical remote sensing can estimate concentrations of, and changes in, parameters such as chlorophyll-a (Chl-a), phycocyanin, and turbidity, which are common indicators used to estimate the presence and intensity of HABs*

**4. Objectives**

In order to attempt to address United Nations SDGs 3(good health & wellbeing) & 14(Life Below Water), the research project aims to address the following objectives:

1. To monitor Harmful Algal Blooms and Cyanotoxins from Satellite RS Images data in L. Victoria.
2. To Predict occurrence of cyanobacterial and Harmful algal blooms in the Selected Lake.
3. To associate Automated Internet of Things (IoT) *in situ* sensors, machine learning Applicable in near real-time to enhance the accuracy and speed for *in situ* data analysis.
4. To develop a reporting system to alert on a short-term foreseen bloom.

**5. Study area**

Lake Victoria, with a surface area of about 68,800 KM2 with a mean depth of 40m and maximum depth of 79m ranking the second largest fresh water lake in the world after Lake Superior. Lying between 3o S to 0o 30`N latitude and 31o 40`E to 34o 50`E is distributed among these three East African countries viz Tanzania 51%, Uganda 43% and Kenya the remaining 6%(africangreatlakes.org).

That in place, the lake is privileged to serve about 40 million residents (Dorothy et. al.) in that riparian state, therefore it’s ecological monitoring should be of great geoscientific interest.

Being located in and Equatorial regions, and with climate in the lake basin varying from tropical rain forest with rainfall over the lake for much of the year to a semi dry climate with intermittent droughts over some areas, and provides ambient temperatures varying between 12-26°C it therefore provided ambient host conditions for the growth and development of the Cyanobacteria in this research project.

Figure 1 shows the location and extent of the study area as discussed above.

**6. Methodology**

The comprehensive aim of this project is to come up with a mid-level geo-intelligent system for monitoring and short-term forecasting of cyanobacteria and algal blooms in the area of study. By employing automated Internet of Things (IoT) sensors and Earth Observation (EO) data, the Harmful Algal Blooms (HABs) monitoring and prediction can be achieved in near real-time.

The project idea intends to aggregate Earth Observation Remote Sensing data from Google Earth Engine cloud platform to extract and analyse the presence of Chlorophyll-a pigment.

Parameters to be collected from dataset for Lake Victoria:

1. Ecological water quality parameters including:

● Chlorophyll-a surface concentration

● Suspended Particulate Matter (SPM)

● Lake Surface Temperature (LST)

2. Sustainability indexes (evolution of land cover - land use (1990 - 2020), evolution of pollution release into the lake due to demographic pressure

3. Time series (Long Short-Term Memory) of meteorological observations.

*quality data provide in situ measurements of surface water temperature (◦C), dissolved oxygen (milligrams per liter), pH, turbidity (nephelometric turbidity units (NTU)), Secchi depth (meter), and surface chlorophyll concentration (micrograms per liter). This water quality dataset covers the time period between May 2013 and November 2017. Chl-a concentration measurements are used in the present study for the development and validation of the SVM predictive models. The USACE water quality data were collected in the months of May, June, July, August, September, and October. The Chl-a concentrations varied from 1.3 to 63.1 µg/L, with an average value of 9.9 µg/L and a standard deviation of 7.8 µg/L. There are seasonal changes in the mean values of the Chl-a samples, indicating the role of climate and some other seasonal factors such as agriculture activities in shaping Chl-a concentrations in these lakes. The average Chl-a values (µg/L) gradually increase from May (7.7) to June (8.2), July (8.4), August (9.1), and reach the peak in September (11.7). It then drops in October (8.4) to a similar level as in June and July*

*This work subsequently led to a large number of remote sensing detection, monitoring and forecasting systems developed for more recent sensors and satellites such as MODIS-Aqua, MODIS-Terra, SeaWiFS, MERIS and more recently Sentinel-3 [2]. The methods used for detection, monitoring and forecasting of HAB events have included: reflectance band-ratio based detection; reflectance classification (using anomaly detection); satellite product-based detection (using thresholds etc.); and spectral band differences. The most successful and important methods for HAB detection have used spectrally derived products such as Chl-a (Chlorophyll concentration estimate), as phytoplankton increases the backscattered light within pigment absorption spectral frequencies. An excellent review of these historical and current methods, sensors and satellites is given by Blondeau-Patissier et al. [2].*

*Previous remote sensing based HAB detection methods have, in the majority of cases used spatially isolated and single satellite sensor data samples. Many methods have been developed for HAB detection utilising a wide range of satellite sensors and bands. Many common methods of HAB detection are currently based on Chlorophyll concentration products, as Chl-a is in many cases, a very accurate proxy of local algal activity. Phytoplankton is the primary water constituent [16], [17] thus, Chl-a can often be accurately estimated using the water-leaving reflectance using relationships (such as remote sensing band-ratios) for data from sensors such as SeaWiFS, MERIS and MODIS [18], [19].*

*These simplistic methods in many cases suffer from a large quantity of false positive detections. The most effective updates to these methods further consider measures of Carbon Dissolved Organic Matter (CDOM) utilising backscattering data from SeaWiFS and MODIS*

Besides that, meteorological data (for the last few years together with water quality data supplied by the Lake Victoria Basin Health Monitoring. These data will be used to identify historic occurrences of algal and cyanobacterial blooms in that specified Lake.

 The result will be analysed on the fly and a short Early Warning System in the form of a text SMS will be relayed to the authorities concerned.

**7.Expected Results**

It is expected that upon successful completion of this project, there should be The system will then be usable in near real-time through the IoT utilizing incoming *in-situ* data to provide a short-term probabilistic forecast of the likelihood of a bloom, dependent on the weather conditions on previous and current trends.

1. Chlorophyl-a Geographical Maps associating the occurrence of the Harmful Algal Blooms and Cyanobacteria.
2. Automated system that monitors and reports geo-tagged data
3. Reported confirmation alert Text SMS reporting in near-real time the *in-situ* status from the sensors.
4. Time Series predictive model on any looming bloom.

**References:**

# *Michael A., GeoJango Maps, 5 Largest Lakes in The World.* Retrieved on May 16, 2021 <https://geojango.com/blogs/explore-your-world/largest-lakes>

National Library of Medicine*, Detection of bacteria associated with harmful algal blooms from coastal and microcosm environments using electronic microarrays*. Retrieved on May, 15 2021, <https://pubmed.ncbi.nlm.nih.gov/17298369/>