SPATIOTEMPORAL MODELLING & AUTOMATED *IN-SITU* SENSORS TO MONITOR HARMFUL ALGAL BLOOMS (HABS)

Case Study Lake Victoria

by

Okomo Jacob Okello

Project report submitted to the department of Geomatic Engineering and Geospatial Information Systems degree of Bachelor of Science in Geospatial Information Sciences (GIS), 2021.

Department of Geomatic Engineering and Geospatial Information Systems (GEGIS)

DECLARATION

I declare that this project is my own work and has not been submitted by anybody else in any other university for the award of any degree to the best of my knowledge.

Sign………………………………… Date………………………………………...

Jacob Okello Okomo

ENC222-0149/2017

Department of Geomatic Engineering and Geospatial Information Systems (GEGIS)

Jomo Kenyatta University of Agriculture and Technology

CERTIFICATION

This project has been submitted for examination with my approval as the candidate's supervisor.

Sign……………………………. Date ………………………………………………

Dr. Eunice Nduati

Senior Lecturer, GEGIS

Department of Geomatic Engineering and Geospatial Information Systems (GEGIS)

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Abstract

This is meant to cover the whole project content in brief. I therefore request to update this section at project completion and closure stage.

-Thank you

Table of contents

List of figures

List of tables

Acronyms and abbreviations

1.	DO	Dissolved Oxygen
2.	GDP	Gross Domestic Product
3.	HAB	Harmful Algal Bloom
4.	FAI	
5.	FLH	
6.	IoT	Internet of Things
7.	KMFRI	Kenya Marine and Fisheries Research Institute
8.	KTN	Kenya Television News
9.	LSAT	Lake Surface Air Temperature
10.	LSWT	Lake Surface Water Temperature
11.	MCI	
12.	MERIS	MEdium Resolution Imaging Spectroradiometer
13.	ML	Machine Learning
14.	MODIS	MODerate Resolution Imaging Spectrometer
15.	OLI	Operational Land Imager
16.	OC	Ocean Color
17.	Quick-SCAT	
18.	SeaWiFS	Sea-viewing Wide-Field- of-View Sensor
19.	SST	Sea Surface Temperature
20.	TIRS	Thermal InfraRed Sensor
21.	USGS	United States Geological Survey

1 Introduction

1.1 Background

Algal bloom can be defined as “the rapid growth of one or more species which leads to an increase in biomass of the species” (Richardson, 1997). This is normally associated with high concentrations of phytoplankton (algae). If the rapid growth is related to a harmful or toxic species, then it is called Harmful Algal Bloom (HAB). A species can be harmful due to the release of toxic substances e.g., *Cyanotoxins spp*. which are most frequent in the Lake Victoria region (Okello et al., 2011). Often termed as “Red Tides”, HABs have attracted a significant world-wide attention in research over the last two decades (W. Song et al.,2015).

Development, stability, and density of the phenomenon are related to some environmental factors such as wind velocity and direction, Lake Surface Water Temperature (LSWT), Lake Surface Air Temperature (LSAT), Sea Surface Temperature (SST), currents, and adequate nutrient concentration, enough sunlight, warm temperatures (Tang et al, 2006) to be transported over a water body e.g., Kisumu Bay by local circulations and winds especially in large aggregates called *colonies* (Okello & Kurmayer, 2011).

A lot of scholars in the geosciences have put forward a bunch of approaches to detect and monitor HABs in both inland and ocean waters including generating indices from spectral band ratio algorithms e.g., Empirical visible-NIR band ratios (Matthews et al, 2012; Allan et al, 2015), blue-green band ratios (O’Reilly et al., 1998), red-edge (RE) region (690–715 nm) band ratios (Mittenzwey et al., 1992), thermal band based assessment(Tang et al.,2006) can be used to detect and monitor different types of algal blooms.

Currently, remote sensing of HAB detection and monitoring methods are primarily designed for SeaWiFS, MODIS and MERIS (Kurekin et al, 2014) which have a high temporal resolution (about one day), but relatively coarse spatial resolution (250~1130 meters). Although, this category of sensors, allows us to continuously monitor the behavior of the phenomenon, limits us to a detailed examination of HABs and only large scale HABs can be monitored by using them (Blondeau, 2014).

Landsat 8 OLI therefore possesses the great value potential to provide for the retrieval of Chl-a and thermal band from the variety of spectral bands (Allan et al., 2015; Watanabe et al., 2015; Concha and Schott 2016; Manuel et al., 2020).

The advent and uptake of Internet of Things (IoT) further provides for quick development of geo-intelligent automated in-situ sensors that collects near real-time water quality data e.g., LSWT, LSAT which are thermal proxies and indicators of HAB presence thereby enabling a step-change in data availability for HAB monitoring in Lake Victoria.

Therefore, an examination of a high spatiotemporal sensor’s capability to detect and monitor HABs coupled by in-situ sensors technically sounds essential. Landsat 8 high spatiotemporal satellite images (16 days for temporal and 30 & 100 meters for spatial resolution) have made it possible to detect and monitor HABs comparatively more accurately at relatively smaller inland water bodies e.g., Nyanza Gulf of Lake Victoria.

On that regard, this study intends to demonstrate the ability of some spectral features, generated using band 2, 3, 4, 5 and TIR band 10 of L8 OLI in detecting of HABs using empirical statistical methods.

1.2 Motivation and problem statement

Harmful Algal Blooms continue to be of major concern, not only due to their considerable environmental and societal impacts but also a recent significant increase in frequency reported around the world (Hill et al., 2020). HABs can cause severe environmental and human health problems together with associated deterioration in economic value thereby impacting a region's GDP. Environmental impacts include depletion of dissolved oxygen (DO) in the aquatic habitat causing mass fish stock (Tang et al, 2006) (*Fig 1,2,3 below*). Human impacts include toxic reactions to affected seafood and in extreme cases, fatalities. Economic impacts include adverse effects on coastal based industries e.g., fishing (Smith et al., 2019), tourism (*Fig 4*).

During the last two decades, coastal regions of Lake Victoria such as Nyanza Gulf (Kisumu Bay) have shown deterioration in its water quality as seen in severe signs of eutrophication with blooms (Simiyu et al., 2018). Many factors have been cited as causes of HABs but are generally caused by favorable environmental conditions, including increasing nutrient levels-eutrophication (Santoleri et al., 2003), which is associated with urbanization, agricultural malpractices and deforestation (Hecky et al., 2010), water column stratification and/or changes in water temperature. (Gohin F. et al., 2006).

1.3 Justification

Nyanza Gulf is one of the bays of Lake Victoria that is most affected by nutrient enrichment (Gikuma-Njuru, P. 2013) which is coming from the highly populated catchment with mostly subsistence agriculture (Calamari, D. 1995; Hecky, R.E. 2010). This has led to regular occurrence of bloom-forming cyanobacteria which has been associated with mass fish kills *(Fig 1, 2 & 3 below)* due to depletion of dissolved oxygen (DO) in the aquatic habitats and to some extremes, temporary shutdown of drinking water supply, i.e., from January to March 2004 (Sitoki et al., 2012).

For this purpose, a number of Landsat 8 images with some acquired in a bloom event and some during a no -bloom condition will be quantitatively analyzed. By comparing the statistically derived numerical values of the spectral indices in blooming and non-blooming condition, indices and thermal information will be extracted.

Fig 1: Standard Media Kenya reports through KTN about HABs causing Mass Fish stocks in Dunga Beach Kisumu region in February 2021, (Image: Standard Media KE)

Fig 2: Mass fish stock in Lake Victoria Shores impacted by the HABs (Image: Standard Media KE)

Fig 3: High valued Fish lost to HAB in Lake Victoria Shores (Image Source: KMFRI)

Fig 4: Tourism and therefore Income halted to HABs

1.3 Research identification and Objectives

The main objective of this research is to detect, monitor and report the occurrence of Harmful Algal Blooms (HABs) and Cyanobacteria in Lake Victoria. This is achievable through the following specific objectives:

1.3.1 Research objectives

1 To monitor chlorophyl-a(Chl-a) concentration & Cyanotoxins from L8 OLI data as HAB proxies in L. Victoria from 2015 to 2021.

2 To monitor Lake Surface Water Temperature (LSWT) from L8 TIRS images as another HAB indicator in L. Victoria.

3 To develop automated Internet of Things (IoT) *in situ* sensors, applicable in near real-time to monitor and report geo-tagged Water quality data (e.g., LSWT) from 2021 onwards.

1.3.2 Research questions

The following questions are formulated with respect to aforementioned objectives:

1) Can space based observations systems be used to detect and monitor HABs in Lake Victoria Inland water body?
2) Does HAB occurrence have a direct impact on the LSWT at their point of influence?
3) Can IoT be utilized to monitor HAB occurrences inland water Lakes?

1.4 Study outline

This research study is intended to be divided into 6 chapters whereby the first chapter introduces the study by detailing into the background, motivation and problem statement, objectives and research questions; Chapter 2 will contain the reviewed literature and the research gaps identified and how this research intends to address the identified gaps. Further, Chapter 3 will show the data and methods used in the study with Chapter 4 highlighting the results for the findings from the methods. Chapter 5 will discuss on the findings and finally, Chapter 6 will conclude and recommend for future research that might not be addressed at this level of geoscientific expertise.

2. Literature review

2.1 A Synthesis on the Occurrence and Negative Impacts of HABs

During the last few decades (especially the last two decades), eutrophication of lakes as a result of HABs has been a common environmental problem observed in both freshwater (Jiang et al. 2015; Luo et al. 2016) and salty water bodies (Blondeau-Patissier et al., 2014), raising a global concern due to their ability to rapidly produce various hepatotoxic and neurotoxic substances (W. Song et al.,2015).This has so been the case even at a local water bodies like Lake Victoria in East Africa which showed a potential significance of algal blooms reported as early as 1980's (Ochumba, 1984).

Proliferation of algae causes eutrophication of freshwater lakes under certain environmental conditions and float on the water surface to cause abnormal watercolor amongst a variety of aquatic-related threats (Huisman et al. 2005; Liu and Yang 2012; Qin et al. 2016). These phenomena have been observed to be severely detrimental to aquatic environment in global inland water bodies which generally follows to the growing discharge of domestic or industrial wastewater as well as agriculture and fertilizer runoff (Glibert et al., 2005; Tang et al, 2006).

The ecological phenomenon has apparently been related to a variety of socioeconomic havocs like widespread occurrence of mass fish stocks and fish booms (Ochumba, 1985, 1987; Caballero et al., 2020). Being actively photosynthetic, the blooms, not only deplete the dissolved oxygen (DO) in waters that result in mass death to water lives but also release toxins, e.g., microcystin, that cause health risks to wildlife, livestock, pets, and humans who get in contact with the HABs (Hallegraeff, 1993), affecting the safety of drinking water supply (Guo 2007; Qin et al. 2010) leading to the disruption of the water food chain as it affects both trophic levels in the chain (Diaz and Rosenberg 2008).

Furthermore, surface foams or scums formed by CyanoHABs and their odorous compounds foul up water quality and surrounding recreational environment (Anderson et al., 2002).

2.2 Space-based Optical Remote Sensing in the Monitoring of Chlorophyll-a as an indicator of HAB event.

Numerous geoscience scholars have observed that space-based observations are of great significance and importance in quantifying in detailed the spatial distributions of HABs in inland water bodies on a regular basis.

Near-surface concentration of chlorophyll-a (Chla), a proxy for HAB, has been observed and quantified in aquatic ecosystems through optical remote sensing for many years (Clarke et al., 1970; Wezernak et al., 1976; Smith and Baker 1982; Gordon et al., 1983; Bukata et al., 1995; Tang et al., 2006; Gitelson et al., 2007; Allan et al., 2015; Watanabe et al., 2015; Concha and Schott 2016). This technique has led to the routine production of global Chl-a distributions for the oceans for more than two decades (Manuel et al., 2020).

A variety of heritage algorithms have been developed in that regard. For example, the blue-green band-ratio models have been used to estimate Chl-a (Gordon et al., 1980; O'Reilly et al., 1998), which are realistic representations of biomass in ecosystems where other constituents, such as colored dissolved organic matter (CDOM), co-vary with Chl-a. In optically complex inland and coastal waters however, the color of water is further modulated by the presence of organic and inorganic particles, as well as dissolved matter (Han et al., 1994; Harding et al., 1994) that do not generally co-vary with phytoplankton, rendering retrievals of Chl-a far more challenging task (Mittenzwey et al., 1992).

To improve estimates of Chl-a in these turbid and eutrophic environments, more sensitive methods have been developed. For example, spectral bands within the red-edge (RE) region (690–715 nm) (Vos et al., 1986; Mittenzwey et al., 1992), combined with red bands have manifested at a greater confidence to correlate well with Chl-a in turbid and/or eutrophic waters (Munday and Zubkoff 1981; Gower et al., 1984; Khorram et al., 1987; Gitelson 1992; Rundquist et al., 1996; Gitelson et al., 2007).

The Operational Land Imager (OLI) aboard Landsat-8 which was launched in February 2013 to capture changes at relatively high (30 m) spatial resolution which is relatively high (Irons et al., 2012) has offered significant improvements in both data quality and quantity (i.e., both spectral and spatial coverage) over other previous heritage instruments (Markham et al., 2014; Pahlevan et al., 2014; Markham et al., 2015) and is relatively capable of monitoring bimonthly HAB dynamics (Pahlevan et al., 2014; Markham et al., 2015).

Several methods have been developed to retrieve Chl-a from the four OLI visible bands (Allan et al., 2015; Watanabe et al., 2015; Concha and Schott 2016; Manuel et al., 2020).

2.2.1 Retrieval of Chl-a from Landsat 8 OLI Optical Spectral Bands

O'Reilly et al. (1998) observed that for satellite missions that do not support measurements in the RE portion of the EMR Spectrum, Chl-a algorithms tend to rely on blue-green band ratio algorithms coupled by some complex ML approaches. This is true even for Landsat-8 (Le et al., 2013; Freitas and Dierssen 2019).

Most research on Chl-a retrieval has focused on instruments like the MERIS, inherently equipped with RE bands (Gitelson 1992; Gower et al., 2005; Gitelson et al., 2007); however, these algorithms are not advisably applicable to missions without such measurements (RE) like MODIS (Esaias et al., 1998), VIIRS (Wang et al., 2014), Geostationary Ocean Color Image (GOCI) (Ryu et al., 2012) and Landsat 8 (Snyder et al., 2017). Thus, the adoption of the widely used Chl-a estimation algorithms of the band-ratio Ocean Color (OC) family (e.g., OC3), (Neil et al., 2019) which has been proven to improve Chl-a retrieval from OLI products in highly turbid or eutrophic lakes (Cao et al., 2020).

Regional and local algorithms specific to OLI imagery have also been attempted with some success in lakes and reservoirs (Allan et al., 2015; Watanabe et al., 2015; Snyder et al., 2017).

2.3 Capabilities of Space-based observations in the Monitoring of Lake Surface Air Temperature as an indicator of HAB event.

With the advent of thermal imaging remote sensing, it has been observed that optically derived Chl-a data in conjunction with Sea Surface Temperature (SST) observations derived from space borne sensors like the Advanced very high-resolution radiometer (AVHRR) have great potential to monitor (Tang et al., 2003a).

Thermal infrared bands are able to measure the amount of infrared radiant heat emitted from land surfaces and the radiant temperature of waterbodies that have environmental and economic import (Anderson, J. et al., 1984; Haakstad, M. et al., 1994; River S et al., 2004).

It has been noted that Satellite Sea Surface Temperature (SST) data are often used in combination with chlorophyll-a to relate to bloom events (Villareal et al., 2012) at a higher accuracy. This has also been observed in inland water bodies where Lake Surface Air and Water Temperatures (LSAT and LSWT) are taken in considerations (Thomas et al., 2012; Shi and Wang, 2007). Peñaflor et al. 2007 also examined the correlation of seasonal phytoplankton bloom in the Luzon Strait off the Philippines using MODIS Chl and SST, in addition to Quick-SCAT wind data. Similar findings were also documented by Binding et al., 2012, 2013 by using MERIS MCI in particular by focusing in the FLH and FAI, as well as other indices, used in conjunction with satellite estimates of Chl-a and SST to improve our image analysis in a very efficient way.

Blooms of blue-green algae are reportedly often associated with increase in water temperatures (Hutchinson, 1967). During a bloom observed in Lake Victoria, the average Lake Surface Water temperature of the open waters rose from (23.9-24.8°C) to (26.9–29.5°C) in May of 1986 within two weeks of the bloom period (Kilham, 1991; Gasse, Talling & Kilham, 1994).

2.4 A Review of the Potential of Smart IoT Solutions in Location-based Water quality monitoring.

The advent of smart solutions and of Internet of Things (IoT) has lately shown an escalating curve in their great capability to monitor water quality particularly with advancement in communication technology(cit). Being able to remotely gather and disseminate the in-situ water parameters e.g., Lake Surface Water Temperature (LSWT) and Lake Surface Air Temperature (LSAT) which are correlated with an algal bloom event in inland water bodies.

In this regard, legislations have been passed through the relevant government and non-governmental agencies for example the Kenya Marine and Fisheries Research Institute (KMFRI), African Great Lakes to set thresholding standards in water quality parameters that relate to HAB events. These parameters include Lake Victoria Surface Air Temperature which is set to vary with the proximity to the shore, (6.5-8.5), Suspended solids (30 mg/L), Pathogens and bacteria (Nil/100ml), Fluoride (1.5mg/L), Total dissolved solids (1200mg/L), Ammonia (0.5 mg/L), Nitrates (10mg/L), among many other water quality parameters.

In-situ Water quality monitoring is defined as the collection of information at set locations and at regular intervals in order to provide data which may be used to define current conditions, establish trends, etc. (Niel et al., 2016; Muinul et al., 2014; Jianhua et al., 2015). This can be used to ascertain the abnormalities in the pre-set standards or provide early warning identification of hazards.

The proposed power efficient, simple solution *in-situ* monitoring system provides near real time analysis and dissemination of LSAT and LSWT collected. The system also provides an alert to a remote user, e.g., Lake Water Authorities who are remotely located in the offices when there is a significant deviation of water temperature from the pre-defined set of standard values which is a associated with a bloom.

Integration of various methodologies such as the Risk Quotient Approach to show color coded hazards and each hazard level for each parameter assessed at each location e.g., Surface temperature at a given location mapped using Geographical Information Systems (Wal, Abdul, Muhammad et al, 2019).

Location-based approach in assessing lake and water resource pollution has been implemented by Waspmote in . Sample points were established using field survey, lab analyses and geospatial techniques to monitor the various water quality parameters. The results were tables, graphs and maps showing the concentrations of the parameters.

Boddula et al. (2017) proposed a wireless sensor system, CyanoSense, which provided a low footprint, low power and low-cost solution for the monitoring algal bloom remotely in Lake Oconee, Georgia, USA.

A Smart GIS-based in-situ model for assessing aquifer vulnerability was implemented in Kakamigahara Heights, Gifu Prefecture, central Japan (Babiker et al. 2010)

A GIS-based emergency response system for sudden water pollution was developed in China. (Ma, Xu, and Wang 2014; Zhang 2014). It uses GIS technology and a hydraulic water quality model to represent the levels and extents of pollution. Maps showing the spatial distribution of the sample points are generated.

3. Materials and methods

3.1 Study area

Lake Victoria, with a surface area of about 68,800 KM^2 and an average depth of 40m at a maximum depth of 79m ranks the second largest fresh water lake in the world after Lake Superior and the Largest in Africa. Lying between 3° S to 0° 30` N latitude and 31° 40` E to 34° 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 as economical home of about 40 million residents (Calamari et al.,1995) in those riparian reserves. These millions of individuals solely bank on the lake for all aspects of their daily economic livelihood ranging from, fishing, agriculture, and industrial applications just to barely highlight but a few. On that regard, it's ecological monitoring should be of great geoscientific interest.

Being located in Equatorial regions of the globe, the lake has an alternating climatic condition varying from tropical rain forest with rainfall over the lake for a better portion of the year to a semi dry climate with sporadically discontinuous droughts over some locations.

This provides ambient temperatures varying between 12-26°C which therefore provides an optimum host condition for the growth and development of the *Cyanobacteria spp.* in this scope (Okello et al., 2011).

Figure 5 shows the location and extent of the extract of the study area particularly relevant to this study.

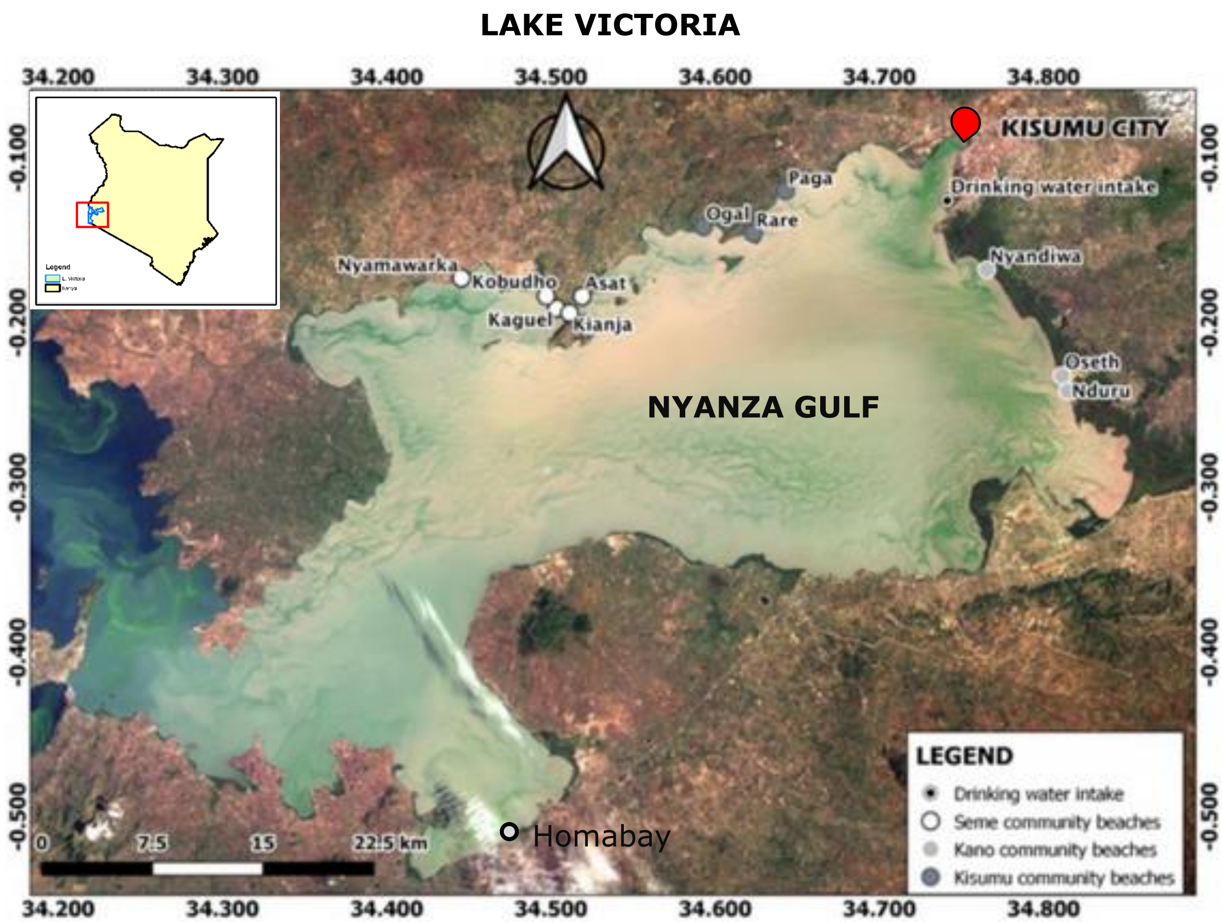

Fig. 5 Map of Winam Gulf with study sites.

3.2 Data

Table 1: Data Sources and their roles

Data Type	Source	Role/Use
Landsat 8 OLI (30m, 16 days)	Google Earth Engine (2015-2021)	Spatiotemporal HAB Monitoring
Landsat 8 TIR (100m, 16 days)	Google Earth Engine (2015-2021)	Lake Surface Water Temperature Monitoring (LSWT)
Meteorological Data	Kenya Marine & Fisheries Research Institute-KMFRI (2015-2021)	Water Quality assessment
Shapefiles	Geodatabase of Global Administrative areas- GADM	Delineate the Study area
In-Situ Data	In-situ Sensors 2021 Onwards	Continued In-Situ Algal Monitoring

Table 2: Tools and Materials used in the study

Tool/Material	Role	Availability
Google Earth Engine (GEE)	**Geocomputation & Processing**	**Freely Available**
QGIS, R & Python	**Further Analysis & Maps**	**Free**
Microcontroller & Sensors	**In-Situ data Monitoring**	**Local Purchase**
KiCAD	**Design the Schematics & basic Circuits**	**Free & Open source**

3.3 Methodology

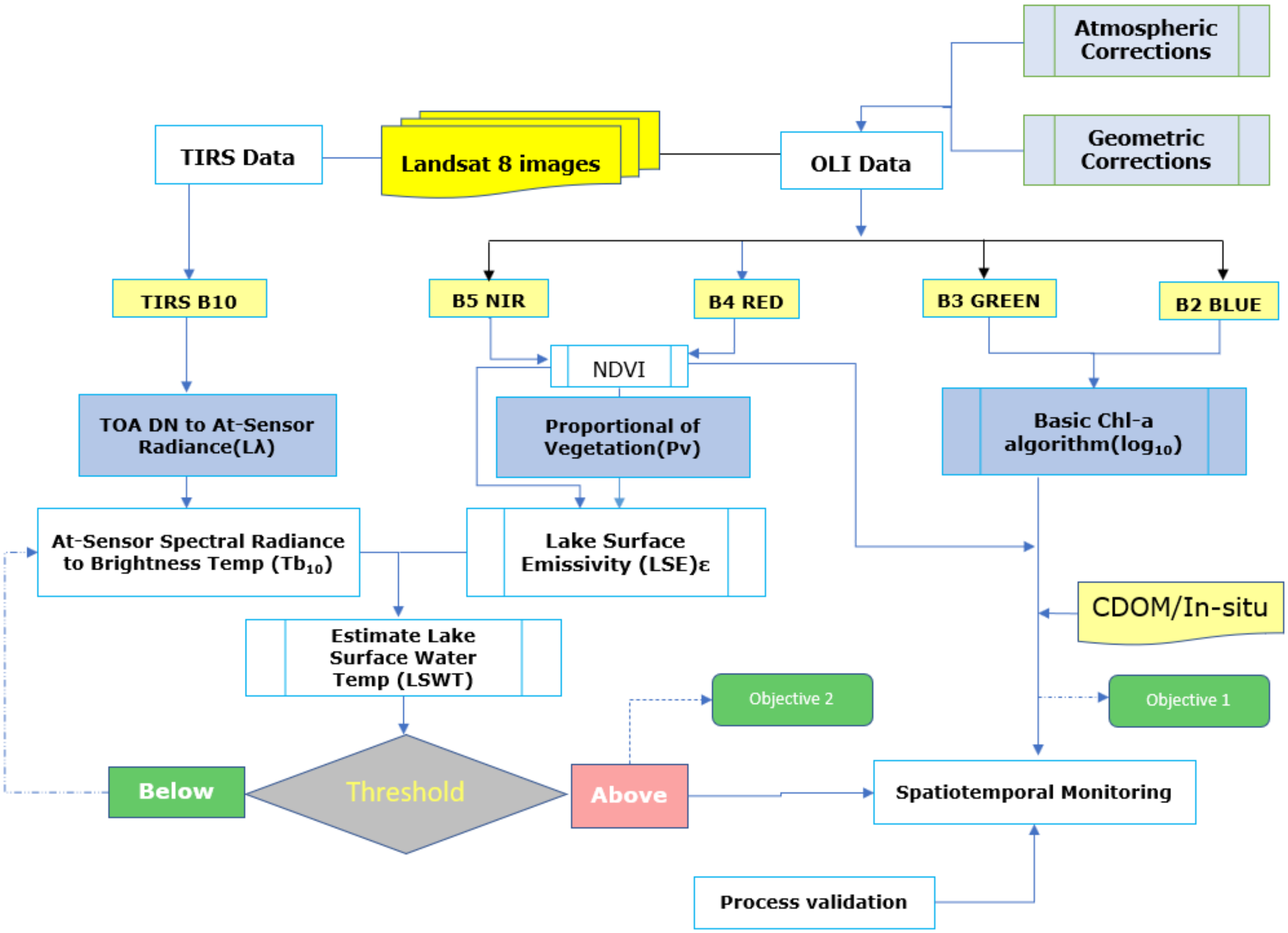

Fig 6: Overall Methodology Workflow for Objectives 1 and 2

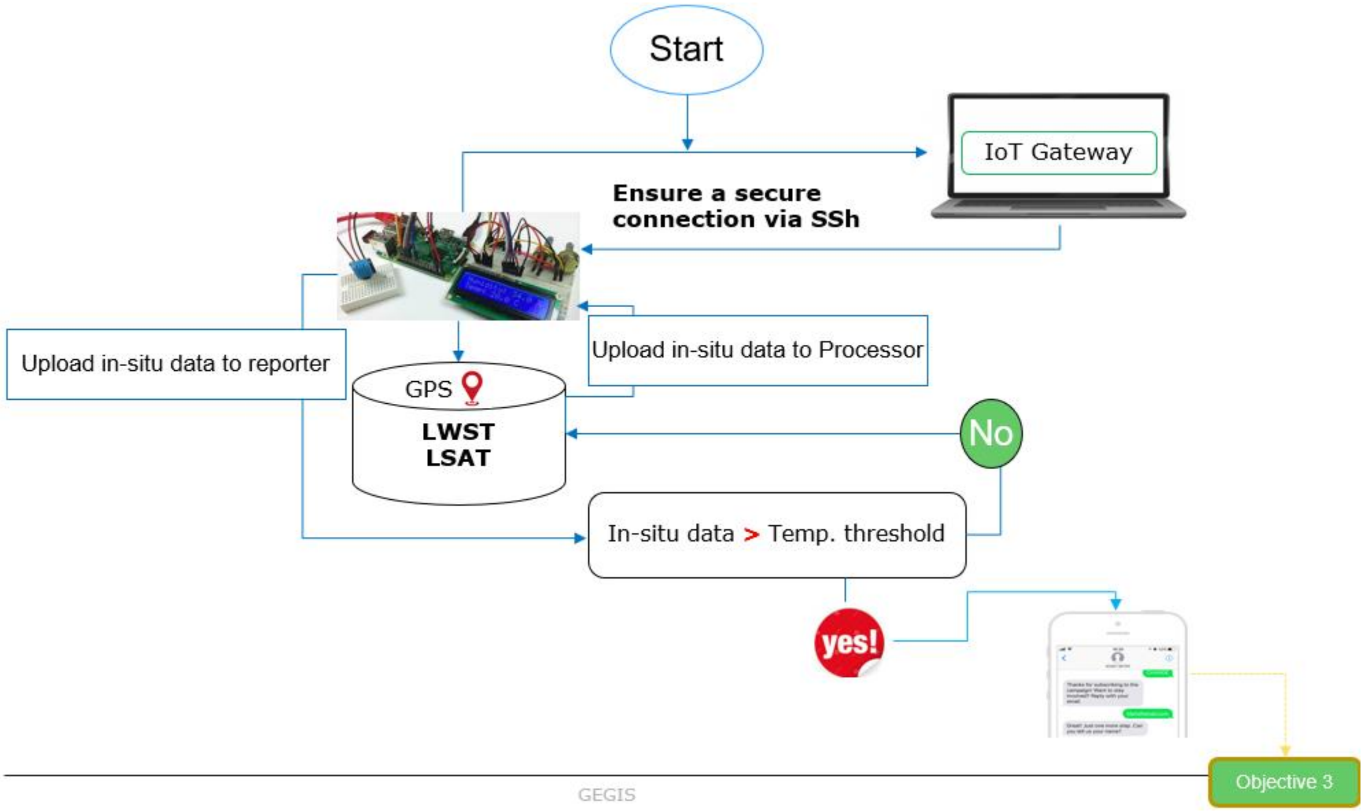

Fig 7: Overall Methodology Workflow for Objectives 3

References

Allan, M. G., Hamilton, D. P., Hicks, B., and Brabyn, L. (2015). Empirical and semi-analytical chlorophyll-a algorithm for multi-temporal monitoring of New Zealand lakes using Landsat. Environ. Monit. Assess. 187, 364. https://doi:10.1007/s10661-015-4585-4

Anderson, J.; Wilson, S. (1984) The physical basis of current infrared remote-sensing techniques and the interpretation of data from aerial surveys. Int. J. Remote Sens., 5, 1–18.

Babiker, Insaf, Mohamed, Mohamed, Hiyama, Tetsuya, Kato, Kikuo, (2010) A GIS-based model for assessing aquifer vulnerability in Kakamigahara Heights, Gifu Prefecture, central Japan.

Blondeau-Patissier, D., Gower, J. F. R., Dekker, A. G., Phinn, S. R., & Brando, V. E. (2014). *A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans*. *Progress in Oceanography*, *123*, 123–144. https://doi.org/10.1016/j.pocean.2013.12.008

Boddula, V., Ramaswamy, L., & Mishra, D. (2017). CyanoSense: A Wireless Remote Sensor System Using Raspberry-Pi and Arduino with Application to Algal Bloom. *2017 IEEE International Conference on AI & Mobile Services (AIMS)*, 85–88. https://doi.org/10.1109/AIMS.2017.19

Caballero, I., Fernández, R., Escalante, O. M., Mamán, L., & Navarro, G. (2020). New capabilities of Sentinel-2A/B satellites combined with in situ data for monitoring small harmful algal blooms in complex coastal waters. *Scientific Reports*, *10*(1), 8743. https://doi.org/10.1038/s41598-020-65600-1

Calamari, D.; Akech, M.O.; Ochumba, P.B.O. (1995) *Pollution of Winam Gulf, Lake Victoria, Kenya: A case study for preliminary risk assessment*. Lakes Reserv. Res. Manag. 1, 89–106.

Chorus and J. Bartram (1999), Toxic cyanobacteria in water. A guide to their public health consequences, monitoring and management. London: E & FN Spon,388p.

Gikuma-Njuru, P.; Hecky, R.E.; Guildford, S.J.; MacIntyre, S. (2013) *Spatial variability of nutrient concentrations, fluxes, and ecosystem metabolism in Nyanza Gulf and Rusinga Channel, Lake Victoria (East Africa)*. Limnol. Oceanogr.58, 774–789.

Gitelson, A. (1992). The peak near 700 nm on radiance spectra of algae and water: relationships of its magnitude and position with chlorophyll concentration. Int. J. Rem. Sens. 13, 3367–3373. doi:10.1080/ 01431169208904125

Gohin F. et al., (2003) “Satellite and in situ observations of a late winter phytoplankton bloom, in the Northern Bay of Biscay.” Continental Shelf Research, vol. 23, pp. 1117–1141,

Haakstad, M.; Kogeler, J.; Dahle, S. (1994) Studies of sea surface temperatures in selected northern norwegian fjords using Landsat TM data. Polar Res., 13.

Hecky, R. E., Mugidde, R., Ramlal, P. S., Talbot, M. R., & Kling, G. W. (2010). Multiple stressors cause rapid ecosystem change in Lake Victoria. Freshwater Biology, 55, 19–42. https://doi.org/10.1111/j.1365-2427.2009.02374.x

Irons, J. R., Dwyer, J. L., and Barsi, J. A. (2012). The next Landsat satellite: the Landsat data continuity mission. Rem. Sens. Environ. 122, 11–21. doi:10.1016/j. rse.2011.08.026

Hill, P. R., Kumar, A., Temimi, M., & Bull, D. R. (2020). HABNet: Machine Learning, Remote Sensing Based Detection and Prediction of Harmful Algal Blooms. ArXiv:1912.02305 [Cs, Eess]. http://arxiv.org/abs/1912.02305

Khalili, M. H., & Hasanlou, M. (2019). HARMFUL ALGAL BLOOMS MONITORING USING SENTINEL-2 SATELLITE IMAGES. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-4/W18, 609–613. https://doi.org/10.5194/isprs-archives-XLII-4-W18-609-2019

Kurekin, A.A., Miller, P.I., Van der Woerd, H.J., (2014). *Satellite discrimination of Karenia mikimotoi and Phaeocystis harmful algal blooms in European coastal waters: merged classification of ocean colour data*. Harmful Algae 31, 163–176

Mittenzwey, K. H., Ullrich, S., Gitelson, A., and Kondratiev, K. (1992). *Determination of chlorophyll a of inland waters on the basis of spectral reflectance*. Limnol. Oceanogr. 37, 147–149. *https://doi:10.4319/lo.1992.37.1.0147*

Ochumba, P.B.O. (1987) *Periodic massive fish kills in the Kenyan part of Lake Victoria. Water Qual. Bull.12* ,119-122, 130.

Okello, W., & Kurmayer, R. (2011)*. Seasonal development of cyanobacteria and microcystin production in Ugandan freshwater lakes: Seasonal development of cyanobacteria and microcystin production. Lakes & Reservoirs: Research & Management,* 16(2), 123–135. https://doi.org/10.1111/j.1440-1770.2011.00450.x

O’Reilly, J. E., Maritorena, S., Mitchell, B. G., Siegel, D. A., Carder, K. L., Garver, S. A., et al. (1998). Ocean color chlorophyll algorithms for SeaWiFS. J. Geophys. Res. 103, 24937–24953. https://doi:10.1029/98jc02160

Richardson, K., 1997. Harmful or exceptional phytoplankton blooms in the marine ecosystem. Advances in Marine Biology 31, 301–385

River, S.; Sub-Basins, S.R. (2004) *Aerial Surveys Using Thermal Infrared and Color Videography; University of California*: Davis, CA, USA.

Santoleri R. et al., “Year-to-year variability of the phytoplankton bloom in the southern adriatic sea (1998-2000): sea-viewing wide field-of-view sensor observations and modeling study,” Journal of Geophysical Research, vol. 108, p. 8122, 2003

Simiyu, B., Oduor, S., Rohrlack, T., Sitoki, L., & Kurmayer, R. (2018). Microcystin Content in Phytoplankton and in Small Fish from Eutrophic Nyanza Gulf, Lake Victoria, Kenya. Toxins, 10(7), 275. https://doi.org/10.3390/toxins10070275

Smith, R. B., Bass, B., Sawyer, D., Depew, D., & Watson, S. B. (2019). Estimating the economic costs of algal blooms in the Canadian Lake Erie Basin. Harmful Algae, 87, 101624. https://doi.org/10.1016/j.hal.2019.101624

Sitoki, L.; Kurmayer, R.; Rott, E(2012). Spatial variation of phytoplankton composition, biovolume, and resulting microcystin concentrations in the Nyanza Gulf (Lake Victoria, Kenya). Hydrobiologia, 691, 109–122.

Song, W., Dolan, J., Cline, D., & Xiong, G. (2015). Learning-Based Algal Bloom Event Recognition for Oceanographic Decision Support System Using Remote Sensing Data. Remote Sensing, 7(10), 13564–13585. https://doi.org/10.3390/rs71013564

Tamatamah, R. A., Hecky, R. E., & Duthie, HamishC. (2005). *The atmospheric deposition of phosphorus in Lake Victoria (East Africa)*. Biogeochemistry, 73(2), 325–344. https://doi.org/10.1007/s10533-004-0196-9

Tang, D., Kawamura, H., Oh, I. S., & Baker, J. (2006). *Satellite evidence of harmful algal blooms and related oceanographic features in the Bohai Sea during autumn 1998*. Advances in Space Research, 9.

Waspmote- Wireless Sensor Networks Open Source Platform. https://www.cooking-hacks.com/documentation/tutorials/waspmote #waspmote ps 2 8 4

Watanabe, F. S., Alcantara, E., Rodrigues, T. W., Imai, N. N., Barbosa, C. C., and Rotta, L. H. (2015). *Estimation of chlorophyll-a concentration and the trophic state of the Barra Bonita hydroelectric reservoir using OLI/ Landsat-8 images.* Int. J. Environ. Res. Publ. Health 12, 10391–10417. doi:10.3390/ijerph120910391

W. Song, J.M Dola, D. Cline and G. Xiong. (2015). Learning-based algal bloom event recognition for oceanographic decision support system using remote sensing data, Remote Sensing, vol. 7, no. 10, pp. 13 564–13 585.

Appendix

Add any extra materials that could not fit in the main text of your write up and is relevant to your study.