**INTRODUCTION & SOME GOOD LITERATURE REVIEW**

*Relevance of the background (2)*

*Problem statement clear and concise (2)*

*Importance of the study/Justification (2)*

*Research questions (2)*

*Research objectives (2)*

**Background**

**Def**

Algal bloom can be defined as “the rapid growth of one or more species which leads to an increase in biomass of the species”. (Ricardson, 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 “Red Tides”, HABs have attracted a significant world-wide attention over three decades in research over the last two decades (W. Song et al.,2015).

**Impacts of HABS**

They continue to be of major concern, not only due to their considerable environmental and societal impact 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). 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).

**Development and Spread**

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).

Development, stability, and density of the phenomenon are related to some environmental factors such as wind velocity, 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 the Kisumu Bay by local circulations and winds especially in large aggregates called colonies (Okello & Kurmayer, 2011).

**Detection (What others have done versus what you want to do)**

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 (Gitelson et al, 1992; Shangumam, 2006; Carvalho, 2011; Siswanto et al, 2013; Shanmugam, 2008; Zhao et al, 2010; 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 (Vos et al., 1986; Mittenzwey et al., 1992), thermal band based assessment(Tang et al.,2006) can be used to detect and monitor different types of algal blooms.

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

**Research gaps**

The status quo in remote Sensing of HAB detecting and monitoring methods are designed for SeaWiFS, MODIS and MERIS (Kurekin et al, 2014) which have a high temporal resolution (about one day), but relatively poor 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). Furthermore, the space-based observations are highly attenuated by atmospheric impacts over the quite humid environments around the water bodies.

**Filling the gap**

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 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.

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 now enables a step-change in data availability for HAB monitoring in Lake Victoria.

**Study area & Methods**

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 and 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 been analyzed. By comparing the statistically derived numerical values of the spectral indices in blooming and non-blooming condition, indices, which the phenomenon causes a noticeable change in their value, will be extracted.

**LITERATURE REVIEW**

*Quality of Chapter (2)*

*Relevance of Literature (2)*

*Appropriate citation/referencing (2)*

*Extensive reading (2)*

*Linkage with Problem Statement (2)*

Articles to read more on:

Tang, D. et al., 2006. Satellite evidence of harmful algal blooms and related oceanographic features in the Bohai Sea during Autumn 1998. Advances in Space Research 37, 681–689

**HARMFUL ALGAL BLOOMS MONITORING USING SENTINEL-2 SATELLITE IMAGES.**

According to (Ricardson, 1997), the definition of an algal bloom is “the rapid growth of one or more species which leads to an increase in biomass of the species”. 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, which can harm human health as well as marine organisms, or deplete dissolved oxygen in the water and causing mortality of marine organisms (Tang et al, 2006).

Development, stability, and density of the phenomenon are related to some environmental factors such as wind velocity, Sea Surface Temperature (SST), currents, and nutrient concentration.

(Tang et al, 2006) reviewed this connection using SeaWiFS ocean color data, AVHRR SST data, and satellite altimeter information. According to their study, HABs generally need adequate nutrient concentrations, enough sunlight and warm water temperatures can be transported by local circulations and winds. There are different ways to detect and monitor HABs such as applying anomaly detecting algorithms to satellite images and products or visual analysis of ocean color data. (Miller, 2006) applied multivariable classification and an anomaly detecting algorithm to SeaWiFS ocean color data to detect HABs. (Kurekin et al, 2014) used an almost similar way to detect the red tide phenomenon occurred in west waters of Netherlands. He used field data along with visual analysis of MODIS ocean color data to classify different types of the area in bloom, no-bloom or harmful bloom categories. Other similar studies include (Shutler et al, 2012), (Banks et al, 2012) and (Anderson et al, 2011). It can be noticed that these researches are based on anomaly detecting, difference detecting and visual analysis methods that only can detect those pixels, which have a different spectral response compared with the background and give no information about the nature of the pixel. Generating an index is another way to detect HABs. (Ahn, Shangumam, 2006) generated an index to detect HABs in optically complex Northeast-Asia coastal waters. The index is presented in equation (1).



where Lw (λ) is the reflectance which is corrected for the skylight reflection and the air-sea interface effects. According to (Siswanto et al, 2013), the need for additional complicated corrections can reduce the applicability of this method. Spectral band ratio algorithms can be used to detect different types of algal blooms. In coastal waters, empirical visible-NIR band ratios are common types of band combinations which have been used by researchers to monitor HABs (Gitelson et al, 2009). (Carvalho, 2011) used empirical blue-green band ratio along with anomaly detecting methods to identify HABs along the west coast of Florida. (Ahn et al, 2006) and (Kahru et al, 2004) are some other researches that rely on spectral band ratio methods. There are also various forms of spectral band difference algorithms which use the visible and NIR portion of the spectrum and have been used by researchers such as (Shanmugam, 2008), (Zhao et al, 2010) and (Matthews et al, 2012) to detect different types of algal blooms. Except for a few research that used high spatial-poor temporal resolution Landsat satellite images only for visual analysis (such as (Yunus, Dou, et al, 2015), most of the HAB detecting and monitoring methods are designed for SeaWiFS, MODIS and MERIS. These sensors despite having a high temporal resolution (about one day), have a poor 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). Therefore, an examination of a high spatial and temporal sensor’s capability to detect and monitor HABs sounds essential.

Sentinel-2 high spatial-temporal satellite images (5~6 days for temporal and 10,20 and 60 meters for spatial resolution) have made it possible to detect and monitor HABs more accurately at small areas. In this research, we have examined the ability of some spectral features, generated using band 2, 3, 4, 8 and 8A of Sentinel-2 satellite images, in detecting of HABs using statistical methods. The case study is east waters of Lantau Island, Hongkong. For this purpose, we used three Sentinel-2 satellite images which one of them is taken in the presence of the HAB and the other two are taken in non-blooming condition. By comparing the numerical value of the spectral indices in blooming and non-blooming condition, indices, which the phenomenon causes a noticeable change in their value, have been extracted. Finally, by classifying the study area using any of the spectral indices and calculating the statistical parameters, determining the accuracy and quality of the classification, the capability of spectral indices in HAB detecting has been discussed.

**Hourly remote sensing monitoring of harmful algal blooms (HABs) in Taihu Lake based on GOCI images**

**Historical/Chronological Interest**

For a long time, it has been the case that eutrophication of lakes is a common environmental problem faced by both freshwater (Jiang et al. 2015; Luo et al. 2016) and salty water bodies.

**Impacts**

HAB is an ecological phenomenon in which algae proliferate in eutrophication freshwater lakes under certain environmental conditions and float on the water surface to cause abnormal watercolor (Huisman et al. 2005; Liu and Yang 2012; Qin et al. 2016). The main HABs in inland waters are cyanobacteria (Pal et al. 2020). The research demonstrates that many cyanobacteria are toxic (Chorus and Bartram 1999). The outbreak of cyanobacteria will not only affect the safety of drinking water supply (Guo 2007; Qin et al. 2010) but also lead to the disruption of the water food chain (Diaz and Rosenberg 2008), and the anaerobic water will affect aquatic organisms (Micheli 1999) and may eventually lead to a decline in water biodiversity (Vonlanthen et al. 2012).

**Need for this project**

Consequently, to eliminate the adverse effects of HABs on the ecological environment and social stability, it is very important to study the temporal and spatial distribution of HABs (Kwon et al. 2020). To effectively control the HABs in Taihu Lake, we must have a clear understanding of the whole process of its occurrence, development, and extinction. The occurrence of HABs in Taihu Lake is marked by large outbreak areas and dramatic changes in time and space, while remote sensing is marked by a large-scale, rapid, continuous, dynamic, visible, and large amount of information (Nazeer et al. 2017).

The identification of HABs in inland lakes based on remote sensing technology can better reflect the temporal and spatial differences and changes of HABs.

**Review**

Many researchers have carried out the monitoring methods of HABs using EOS/MODIS (Moderate Resolution Imaging Spectroradiometer from Earth Observing System), FY3, Landsat TM (Thematic Mapper), and other satellite data and achieved some research results (Cannizzaro et al. 2019; Li et al. 2005; Ma et al. 2009; Xu et al. 2008; Zhou et al. 2008); some scholars have used MODIS satellite data to monitor the HABs in Taihu Lake (Yang et al. 2016); some scholars have used a multi-source satellite data (MODIS, Landsat TM, etc.) to analyze the temporal and spatial distribution of HABs in Taihu Lake (Duan et al. 2012; Duan et al. 2008; Ma et al. 2008; Qi et al. 2014).

**Research gaps**

However, the occurrence of HABs is affected by many factors, such as water quality environment and meteorological conditions, which lead to its rapid development and change (Wang et al. 2020; Wang et al., 2019 b). Conventional remote sensing images cannot meet the needs of dynamic monitoring of HABs in terms of timeliness and dynamic tracking (Hu et al. 2019; Lei et al. 2020).

**Filling the gap**

GOCI is a sensor on Communication, Ocean, and Meteorological Satellite (COMS), the first stationary sea color satellite launched by South Korea in 2010 (Higa et al. 2020; Tang et al. 2019). It can observe the ocean and coastal waters with the spatial resolution of 500 m and the time resolution of updating once an hour and eight times per day (Hu et al. 2019). It has the characteristics of high spatial coverage and high temporal resolution. While recognizing the HABs, it can discover the spatial dynamic change of the HABs in time and study its dynamic migration process in the lake (Noh et al. 2018).

It has important practical significance for monitoring and early warning of the HABs in Taihu Lake. In the near-infrared band, HABs have a high reflectance, while the near-infrared band is a strong absorption band of water. Near-infrared data can clearly distinguish HABs and lake water (Gu et al. 2011), which makes it possible to extract HAB information with high precision by using a mixed pixel decomposition method. The main decomposition models of mixed pixels include the linear mixed spectral model, the fuzzy supervised classification model, and the neural network model (Lv et al. 2003). The most commonly used model of mixed pixel decomposition is the linear mixed model (LMM). The LMM method combined with the NDVI threshold method to extract HABs from GOCI images has not been reported. To address this knowledge gap, in this study, GOCI images are selected to extract HABs by LMM-NDVI, with Taihu Lake as an example. Based on the region of HABs extracted by NDVI, the mixed pixels are decomposed by LMM, and the results are cross-validated with high spatial resolution images (Landsat8 OLI). The hourly distribution of HABs in Taihu Lake was extracted by GOCI images, and the dynamic change was analyzed with meteorological data. Therefore, the purpose of this study is (1) to evaluate the application of LMM-NDVI in the extraction of HAB area, (2) to evaluate whether GOCI image can be used to monitor HABs in Taihu Lake, and (3) to emphasize the importance of high-frequency observation for environmental management and planktonic algae research.

**Monitoring cyanobacterial harmful algal blooms at high spatiotemporal resolution by fusing Landsat and MODIS imagery**

**Impacts**

Toxic Cyanobacteria-rich Harmful Algal Blooms (CyanoHABs) are severe water environmental problems for global inland water bodies concomitant to the growing discharge of domestic or industrial wastewater as well as agriculture and fertilizer runoff (Glibert et al., 2005). The blooms not only deplete the dissolved oxygen 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 due to CyanoHABs exposure (Hallegraeff, 1993). Furthermore, surface foams or scums formed by CyanoHABs and their odorous compounds foul up water quality and surrounding recreational environment (Anderson et al., 2002). Additionally, CyanoHABs are with fast changing characteristics in space and time because of hydrodynamics and many environmental factors, e.g., eutrophication degrees, water temperature, solar illumination, wind stress (Michalak et al., 2013; Wynne et al., 2010).

**Need for this project**

Hence, quantifying the detailed spatial distributions of CyanoHABs in inland water bodies on a regular and frequent basis is of great significance and importance, which requires high spatiotemporal resolution monitoring abilities. CyanoHABs have long been monitored through sensors deployed on buoys to continuously measure various CyanoHAB proxy pigments such as chlorophyll-a (Chl-a) and phycocyanin (PC). However, the spatial distribution of monitoring buoys is usually quite limited over large water bodies because of high installation and maintenance costs in practice (Babin et al., 2008). Therefore, buoy-based observation systems do not provide spatially continuous observations and have limited geographical coverage, especially for large water bodies (Kutser, 2009).

Given that, satellite remote sensing has been used as a more comprehensive and cost-effective way to complement the limitations of buoy-based observation systems (Matthews, 2011), thereby providing a synoptic view of CyanoHABs’ dynamics and life cycles (emergence, growth, senescence, and death) (Wynne et al., 2013).

**State of the art solutions**

Existing remote sensing approaches for algal bloom delineation from satellite imagery include **single band algorithms** (Kutser, 2009), **analytical algorithms** (Stumpf et al., 2016), **band ratio algorithms** (Matthews, 2011), and **baseline algorithms** (Stumpf et al., 2016). Single band algorithms utilize a single feature band of algal blooms to map cyanobacterial extent or biomass (Galat and Verdin, 1989; Ho et al., 2017; Kutser et al., 2006). Analytical models (Kutser, 2004; Simis et al., 2005) utilize multi- or hyper-spectral satellite images to solve backscatter and absorption caused by different substances that are optically active and then map CyanoHAB pigments quantitatively. Band ratio algorithms can be applied to both coarse- and fine-resolution satellites (Kutser, 2009) but they are more commonly used for sensors with a few wide wavelength bands, e.g., Landsat, SPOT, and IKONOS (Matthews, 2011; Stumpf et al., 2016). Band ratios are either directly derived from two spectral bands (Gitelson et al., 1993; Lathrop, 1992; Mayo et al., 1995; Vincent et al., 2004; Yacobi et al., 1995) or calculated as the normalized difference images of two spectral bands (Mishra and Mishra, 2012; Oyama et al., 2015). However, single band, analytical, and band ratio (especially for ratios directly derived from two bands) algorithms require accurate atmospheric correction to obtain water reflectance and are sensitive to sun-glint effects (Stumpf et al., 2016), which could lead to large biases in results without accurate water leaving reflectance (Wang and Shi, 2007).

In contrast, baseline algorithms utilize more than two spectral bands to calculate the second derivative by measuring a reflectance peak height of the spectral feature band(s) of algal blooms above a baseline determined by its/their two adjacent bands at shorter and longer wavelengths (Stumpf et al., 2016; Stumpf and Werdell, 2010).

Since the second derivative calculation can remove the effects of mild sun-glint and atmosphere (Hu et al., 2012; Philpot, 1991), baseline algorithms are more robust than the former three types of methods and are thus widely used in algal bloom monitoring studies (Clark et al., 2017; Lunetta et al., 2015; Wynne et al., 2010).

To date, a number of spectral indices have been developed using baseline algorithms for different satellite sensors at various spatial and temporal resolutions (Stumpf et al., 2016), including **Fluorescence Line Height (FLH)** based on MODIS (Letelier and Abbott, 1996), Maximum Chlorophyll Index (MCI) based on MERIS (Gower et al., 2005), Floating Algae Index (FAI) based on Landsat and MODIS (Hu, 2009), Cyanobacteria Index (CI) based on MODIS and MERIS (Wynne et al., 2013; Wynne et al., 2008), and Maximum Peak-Height (MPH) based on MERIS (Matthews et al., 2012).

While extensive studies have been conducted to monitor algal blooms using multiple satellite sensors across various water bodies, they are all subject to the trade-off between spatial and temporal resolution of satellite sensors (Kutser, 2009; Zhao and Huang, 2017).

**Need For Spatiotemporal Fusion-L8+MODIS**

On one hand, coarse-but-frequent sensors such as Terra/Aqua MODIS provide daily observations but with coarse spatial resolutions (e.g., 250-m to 1000-m) that cannot reveal spatial details of CyanoHABs or delineate CyanoHABs in small lakes. On the other hand, fine-but-sparse sensors such as Landsat-8 OLI can provide more spatial details of algal blooms with their fine-resolution pixels (e.g., 30-m), but their long revisit cycle (e.g., 16 days) makes them insufficient to capture the temporal dynamics of algal blooms (Yacobi et al., 1995).

Therefore, existing methods can only monitor algal blooms either in a coarse but timely manner or a fine but less frequent manner, thereby failing to monitor CyanoHABs with high spatiotemporal resolution (Kutser, 2009).

As a solution to the lack of frequent fine-resolution Earth observations, Spatial-Temporal Image Fusion (STIF) can fuse coarse-but-frequent and fine-but-sparse satellite images to generate fine-and-frequent image series in an effective and low-cost way (Gao et al., 2006; Zhao et al., 2018b). STIF methods utilize spatial detail and temporal change information from prior fine-but-sparse images and coarse-but-frequent images, respectively (Zhu et al., 2016).

Recently, STIF has been used for high spatiotemporal resolution monitoring of water quality, such as Chl-a, turbidity, and total suspended solid, by blending fine-but-sparse (Landsat) and coarse-butfrequent (MODIS) water-leaving reflectance images (Dona et al., 2015; Swain and Sahoo, 2017) with the widely used Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM, Gao et al., 2006). These STIF-based water quality studies work well for downscaling non-spatial changes but perform less effectively when dealing with spatial changes (Zhao et al., 2018b), such as the patchy surface scums formed by CyanoHABs.

Moreover, the existing algae delineation methods based on fine-resolution broad band satellite imagery, e.g., Landsat, do not consider the interference from water suspended sediments, which would lead to overestimation of cyanobacteria loadings if waters have high suspended sediment loadings (Kutser, 2009).

**Seasonal development of cyanobacteria and microcystin production in Ugandan freshwater lakes**

During the last decades cyanobacteria in freshwater have been of general awareness due to their ability to produce various hepatotoxic and neurotoxic substances.

**Impacts**

It is generally agreed that the hepatotoxic microcystin (MCs) are probably the most abundant toxins produced by cyanobacteria in freshwater (1). While the number of taxa that has been found to produce MCs is constantly increasing, the MC-producing genera that are of major importance in phytoplankton have already been identified during the nineties: Anabaena, Microcystis, and Planktothrix (2, 3).

In a recent paper, we could show that cyanobacteria contribute significantly to the phytoplankton of freshwater lakes in Uganda while other algal groups like diatoms, green algae, and cryptomonads are of a relatively minor importance (4).

**Results**

We further concluded that in Uganda the genus Microcystis is favored under more shallow, eutrophic conditions which is in correspondence to the general theory on how abiotic and biotic factors govern phytoplankton associations that have been defined since 1984 (5). In contrast to Microcystis other genera known to produce MCs were found in lower abundance, e.g. Anabaena was abundant in Lake Victoria and one of the Crater Lakes while Planktothrix was not observed.

However, in this earlier study we were unable to monitor the phytoplankton community during different seasons. This issue is of relevance as usually dry seasons with precipitation minima and wet seasons with maximum precipitation have been correlated with changes in phytoplankton composition. Usually, precipitation varies annually from 30 mm to 132 mm in Kasese, western Uganda and 60 mm to 184 mm in Kampala, the L. Victoria basin (Meteorological Department, Entebbe).

This also results in annual changes of water temperature by 5°C in Kasese and 3°C in Kampala. The highest air temperatures are usually recorded during the dry season in February (33°C in Kasese and 29°C in Kampala). During the rainy season (from March to May and August to November), the phytoplankton in shallow lakes will be affected directly by a reduced air temperature (2.5°C in Kasese and 3°C in Kampala), reduced light availability in the water column as well as increased terrestrial run-off. In deeper lakes such as Lake Victoria, the mixing regime will change, as a higher stability of the water column has been described during the dry season June to July (6). These physical changes have a significant effect on phytoplankton community composition.

**A Chlorophyll-a Algorithm for Landsat-8 Based on Mixture Density Networks**

**Literature**

Near-surface concentration of chlorophyll-a (Chla), a proxy for phytoplankton biomass, 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). This technique has led to the routine production of Chla distributions for the global oceans for more than two decades. The heritage algorithms have used blue-green band-ratio models to estimate Chla (Gordon et al., 1980; O’Reilly et al., 1998), which are realistic representations of biomass in ecosystems where other constituents, such as detritus and colored dissolved organic matter (CDOM), co-vary with Chla. 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 Chla a far more challenging task (IOCCG 2000). To improve estimates of Chla in these turbid and eutrophic environments, other 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 shown to correlate well with Chla 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 RE observations, however, are not available in the suite of measurements made by heritage missions – such as Landsat—which have provided the longest record of Earth observation from space (Goward et al., 2017).

The Operational Land Imager (OLI) aboard Landsat-8 was launched in February 2013 to continue Landsat’s mission of monitoring Earth systems and capturing changes at relatively high spatial resolution (30 m) (Irons et al., 2012). This mission has offered significant improvements in both data quality and quantity (i.e., both spectral and spatial coverage) over previous heritage instruments (Markham et al., 2014; Pahlevan et al., 2014; Markham et al., 2015). Several methods have been developed to retrieve Chla from the four OLI visible bands (Allan et al., 2015; Watanabe et al., 2015; Concha and Schott 2016; Manuel et al., 2020), yet Chla retrieval methods in inland and coastal waters using traditional approaches are challenged by optical complexity and high dynamic ranges where water types can range anywhere from very clear to highly turbid and eutrophic (Spyrakos et al., 2018). It is, therefore, critical to continue to formulate novel methodologies that enable the production of viable Chla products from Landsat-8 data for global scientific studies and applications (Snyder et al., 2017).

**Literature review for Objective three**

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.

**Acknowledgements**

Refer to this article located in the HABs directory.

*Water Quality Modelling Using Multivariate statistical analysis and Remote Sensing in South Florida*

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