

Mapping Water Quality Using Remote Sensing Technology: A Case Study of Lake Victoria

Gideon Wafula Simiyu, Josphat Mwatelah

Department of Geomatic Engineering and Geospatial Information Systems, Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya

Email: simiyuleogideon22@gmail.com

How to cite this paper: Simiyu, G. W., & Mwatelah, J. (2025). Mapping Water Quality Using Remote Sensing Technology: A Case Study of Lake Victoria. *Journal of Geoscience and Environment Protection*, 13, 225-252.
<https://doi.org/10.4236/gep.2025.138013>

Received: June 12, 2025

Accepted: August 22, 2025

Published: August 25, 2025

Copyright © 2025 by author(s) and Scientific Research Publishing Inc. This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

Lake Victoria, the largest freshwater lake in Africa and a vital resource for over 45 million people across Kenya, Uganda, and Tanzania, is experiencing escalating environmental degradation due to agricultural runoff, untreated sewage, industrial effluents, and solid waste. These pollutants are driving eutrophication, biodiversity loss, and a rise in waterborne diseases, posing serious ecological and public health threats. This study utilized satellite-based remote sensing and geospatial analytics to assess water quality changes in Lake Victoria over a 20-year period. Cloud-free imagery from the Landsat Collection 2 Tier 1 Surface Reflectance dataset—specifically Landsat 7 ETM+ (2005), Landsat 5 TM (2010), Landsat 8 OLI/TIRS (2013, 2018), and Landsat 9 OLI-2/TIRS-2 (2023)—was analyzed using Google Earth Engine to calculate key spectral indices: Normalized Difference Water Index (NDWI), Chlorophyll Index (CI), Turbidity Index (TI), and Normalized Difference Chlorophyll Index (NDCI). These indices served as proxies for chlorophyll-a, turbidity, and suspended sediment load. Water Quality Index (WQI) values were derived through Python-based scripts, weighted by parameter importance, and classified into four categories: Good, Moderate, Unhealthy, and Very Unhealthy. Results revealed a clear decline in water quality across the lake, particularly near urban centers such as Kisumu, Bukoba, and Entebbe. Notably, 2013 showed an extreme reduction in WQI values, ranging from -8.66 to -330.64 , indicating significant pollution levels. The 2023 imagery continued this trend, with WQI values ranging from $+69.79$ to -130.17 , reflecting very high pollution concentrations, especially in eutrophic zones and sediment-laden estuarine regions. The study demonstrates the effectiveness of remote sensing and Python-driven spatial analytics as a scalable, cost-efficient alternative to traditional water monitoring approaches. It recommends institutional adoption of such technologies along with integration of satellite data with machine learning models, *in-situ* measurements, and community-based monitoring frameworks. Ultimately, informing policy, and

promoting sustainable, cooperative management of Lake Victoria's shared water resources.

Keywords

Water Quality, Water Quality Index (WQI), Satellite Imagery, Water Indices, Lake Victoria

1. Introduction

Water is one of the most vital natural resources, indispensable for human survival, economic development, and the health of ecosystems (Sagan et al., 2020; Taru & Karwankar, 2017; Exposto et al., 2021). Freshwater sources such as rivers, lakes, and groundwater, alongside coastal water bodies, are under increasing threat from pollution (Beshiru et al., 2024) due to rapid industrialization, urban expansion, population growth, and climate change (Hung et al., 2020; Youssef et al., 2021). As pollutants—ranging from industrial discharges and agricultural runoff to untreated sewage—continue to contaminate water bodies, the availability of clean, safe water is diminishing at an alarming rate (Samui et al., 2025; Smith & Rodrigues, 2015). The consequences are dire: over two million deaths occur annually due to waterborne diseases, particularly in regions lacking adequate sanitation and clean water infrastructure (Mitra et al., 2024). Globally, improving water quality is a core goal under the United Nations Sustainable Development Goal 6.3. Yet, traditional water monitoring methods, which rely on fixed, ground-based sampling stations, are limited by cost, time, and spatial coverage (Li, 2016). As a result, there has been a growing shift toward remote sensing (RS) and geographic information systems (GIS) as powerful, cost-effective tools for large-scale, real-time water quality assessment (Huang et al., 2018; Feyisa et al., 2014). These technologies enable the monitoring of optical parameters such as turbidity and chlorophyll with high precision, while advances in machine learning are helping to improve the estimation of non-optical parameters like dissolved oxygen (Yuan et al., 2021; Jonah & Archibong, 2022). Pollution sources are broadly categorized into chemical, biological, nutrient, physical, and solid waste contaminants. Their impacts are far-reaching, affecting human health, aquatic biodiversity, and regional economies (Chow et al., 2020). In many developing countries, poor waste management systems and weak enforcement of environmental regulations worsen the situation. Lake Victoria—a lifeline for millions across Kenya, Uganda, and Tanzania—illustrates the scale of the crisis. Excessive nutrient loading, industrial effluents, sewage discharge, and plastic waste have severely degraded its water quality, leading to eutrophication, declining fish stocks, and heightened public health risks (Jiang et al., 2024).

Addressing such complex challenges requires coordinated action from local, national, and regional stakeholders. Regulatory agencies such as the National Environment Management Authority (NEMA) of Kenya and Uganda, and the National Environment Management Council (NEMC) of Tanzania, along with trans-

boundary institutions such as the Lake Victoria Fisheries Organization (LVFO) and the Lake Victoria Basin Commission (LVBC), play crucial roles in managing and regulating the region's resources. Modern water quality management must combine innovative technologies like RS and GIS with robust policy frameworks to ensure sustainable and equitable access to clean water for current and future generations (Bashir et al., 2020; Fuss, 2019; da Rocha et al., 2021).

2. Evaluation of Lake Victoria's Water Quality Situation

Lake Victoria, the largest freshwater lake in Africa and the second-largest in the world, is a vital natural resource supporting over 40 million people across Kenya, Uganda, and Tanzania. It plays a crucial role in providing water for domestic use, irrigation, fishing, transportation, and hydropower (Haldar et al., 2022). However, in recent decades, the lake's water quality has been severely compromised due to a combination of anthropogenic and natural pressures. Pollution levels have risen dramatically, largely attributed to untreated sewage, industrial effluents, agricultural runoff, and urban waste discharged directly into the lake and its tributaries (Kundu et al., 2017). These pollutants threaten the aquatic ecosystem, endanger public health, and undermine the economic stability of the communities that rely on the lake for their livelihoods (Kuboja et al., 2024). One of the most critical manifestations of Lake Victoria's deteriorating water quality is eutrophication, driven primarily by the excessive loading of nutrients such as phosphorus and nitrogen. Phosphorus levels have increased by approximately 76% since the year 2000, intensifying the frequency and severity of harmful algal blooms (HABs), like cyanobacteria such as *Microcystis* (Kanhai et al., 2021; Brooks et al., 2016). These blooms produce toxins that are harmful to aquatic life and dangerous to human health when the water is used untreated. In some instances, these blooms have caused hypoxic zones areas with depleted oxygen that now occupy up to 40% of the lake bed, disrupting the natural ecological balance and causing large-scale fish kills (Masso et al., 2024). In addition to nutrient enrichment, the lake is burdened by toxic substances such as heavy metals from industrial discharges. Some areas of the lake have reported concentrations exceeding World Health Organization (WHO) limits by over 300% (Roegner et al., 2023). Despite the urgent need for intervention, existing water quality monitoring infrastructure remains inadequate. The current systems suffer from poor spatial coverage, irregular sampling schedules, outdated equipment, and inconsistent measurement of key parameters. Furthermore, monitoring capacity is limited by a lack of funding, insufficient personnel, and a shortage of modern laboratory facilities. Many monitoring stations are under-resourced and incapable of producing real-time data, making it difficult to detect pollution events or to respond promptly. Cross-border coordination between Kenya, Uganda, and Tanzania is weak, leading to fragmented data collection and poor integration of information (Drouillard et al., 2024). The institutional response has also been inadequate. While the LVBC and national agencies such as NEMA have introduced water quality standards and regulation such as

the Water Quality Standards enacted in 2014 enforcement remains weak. Institutional challenges including limited funding, weak regulatory enforcement, and lack of coordination among stakeholders have hampered effective policy implementation (Nalumenya et al., 2024). Climate change compounds these issues by altering rainfall patterns and increasing temperatures, which affect runoff, pollutant dispersion, and lake stratification. These shifts increase the mobility of pollutants and further destabilize the lake's fragile ecosystem. With population growth and expanding economic activity around the lake, the pressure on water resources is expected to intensify in the coming years (Nakkazi et al., 2024). Given the scale and complexity of the water quality challenges facing Lake Victoria, there is a clear need for innovative and scalable solutions. Remote sensing technologies offer a promising alternative to traditional, ground-based monitoring systems. These technologies provide cost-effective, wide-area, and near real-time data on water quality parameters such as turbidity, chlorophyll-a, and surface temperature (Ali et al., 2024). By complementing existing monitoring frameworks, remote sensing can help fill critical data gaps, improve pollution tracking, and support timely and informed decision-making. In summary, the ongoing degradation of Lake Victoria's water quality presents a serious environmental and socio-economic crisis. Inadequate monitoring infrastructure, weak enforcement of regulations, institutional fragmentation, and the growing impacts of climate change are all contributing to the lake's decline (Awange, 2021). To safeguard the health of Lake Victoria and the millions who depend on it, urgent investment in modern, integrated monitoring approaches—especially leveraging remote sensing is essential.

3. Water Quality Mapping Using Spatial Indicators

Various spatial indicators have made it possible to visualize the extent and sources of water pollution in Lake Victoria (Njagi et al., 2022). Enabling more targeted and effective water quality management. Key among these are nutrient concentrations particularly nitrogen and phosphorus which are closely associated with eutrophication and algal blooms caused by agricultural runoff (Batina & Krtalić, 2024). Ground-based sensors have been used to measure parameters such as turbidity, pH, and dissolved oxygen, offering localized insights into the lake's ecological health. Remote sensing technologies also contribute by mapping chlorophyll-a concentrations and surface water temperatures, which indicate biological activity and potential pollution zones; however, their application in the region remains limited (Awange & Ong'ang'a, 2006). In addition, satellite-derived land use and land cover (LULC) data help track urbanization and agricultural practices that intensify pollution loads around the lake (Sitoki et al., 2010). Despite these advancements, the lack of an integrated monitoring framework combining ground-based and satellite data continues to hinder regional water quality efforts. Studies emphasize the need for a robust, unified inventory system to support evidence-based policymaking and transboundary collaboration among the Lake Victoria basin countries (Gordon et al., 1994). Kenya's Water Quality Action Plan and regional

programs like the ASAP project aim to fill these gaps by promoting sustainable practices, stakeholder engagement, and the scaling up of low-cost monitoring technologies. However, translating research findings into policy and practice remains a major challenge, underscoring the need for institutional support and investment in spatial data infrastructure for sustainable water management. An understanding of some of the main causes of water pollution is essential to assess water quality effectively. The Water Quality Action Plan 2022 report, **Table 1**, provides a summary of the key sources and components of water pollution modified from source.

Table 1. Cases and impacts of environmental degradation in lake Victoria Basin.

Emission	Description	Sources	Harmful Effects in Lake Victoria
Land Degradation & Erosion	Loss of vegetation cover, poor farm practices, overuse of agrochemicals.	Upstream forest areas, upstream rural/agricultural areas.	Sedimentation in rivers and streams, decline in water quality, loss of aquatic habitats.
Nutrient Loads	Increase in nitrogen and phosphorus from runoff and untreated wastewater.	Agriculture, urban runoff, wastewater discharge.	Eutrophication, algae blooms, oxygen depletion.
Fecal Loads & Solid Waste	Contamination with fecal matter and solid waste.	Urban areas, informal settlements, towns.	Spread of waterborne diseases, increased treatment costs, loss of fish stocks.
Artisanal Gold Mines	Mining and processing waste.	Upstream urban areas.	Pollution from mercury and heavy metals, groundwater contamination.
Untreated Industrial Effluents	Discharge of harmful industrial waste into water bodies.	Industries near the lake, wetlands.	Pollution of wetlands, toxic impacts on aquatic ecosystems, harm to livelihoods.
Aquaculture Waste	Waste from fish farming practices.	Aquaculture activities around the lake.	Introduction of invasive species, water toxicity, biodiversity loss.
Atmospheric Deposition	Pollutants deposited from the air.	Industrial activities, open burning.	Accumulation of toxins, bioaccumulation in aquatic organisms.
Heavy Metals & Tox-ins	Pollution from hazardous materials like mercury and lead.	Mining, industrial activities, waste disposal.	Bioaccumulation in fish, health risks to consumers, eco-logical disruptions.
Organic & Solid Waste And plastic waste accumulation.	Decomposition of organic material Agriculture, urban and industrial waste.		Oxygen depletion in waterharm to aquatic habitats.

(Modified from source: <https://www.ciwaprogram.org/wp-content/uploads/CIWA-LVB-Learning-Note-1.pdf>).

4. Remote Sensing for Water Quality Mapping

Remote sensing applications for monitoring water quality have evolved significantly since the 1980s, beginning with the Coastal Zone Color Scanner (CZCS) on the Nimbus-7 satellite. Early research, such as by (Sun et al., 2017), demonstrated the utility of satellite-derived ocean color data for assessing chlorophyll

concentrations an important indicator of eutrophication. The launch of NASA's Moderate-Resolution Imaging Spectroradiometer (MODIS) on the Aqua and Terra satellites marked a major advancement, enabling continuous global monitoring of chlorophyll-a, turbidity, and suspended sediments (Gao et al., 2016). Subsequent studies utilized other sensors, such as Landsat-8 for tracking water temperature and sediment (Sent et al., 2021) and Sentinel-2 for detailed assessment of chlorophyll-a and particulate matter in both fresh-water and marine environments. (Zhu et al., 2016). (Attey-Yeboah et al., 2025) further demonstrated MODIS's capability in identifying areas at risk of Harmful Algal Blooms (HABs) in the East China Sea. In African countries, remote sensing has been recognized as a crucial tool for filling data gaps in the water quality monitoring and analysis, especially in Sub-Saharan regions where *in-situ* data are often scarce (Li et al., 2022). (Dube et al., 2015) further demonstrated MODIS's capability in identifying areas at risk of Harmful Algal Blooms (HABs) in the East China Sea. In Africa, remote sensing has been recognized as a crucial tool for filling data gaps in water quality monitoring, especially in Sub-Saharan regions where in-situ data are often scarce (Oyedotun et al., 2025). For instance, Sentinel-2 imagery has been used to assess marine pollution in the Gulf of Guinea, (Karaoui et al., 2019) highlighting its potential for tracking oil spills and runoff. In North Africa, (Were et al., 2013) Karaoui used Sentinel-2 to monitor chlorophyll and particulate matter. Within East Africa, studies have shown growing application: (Nsubuga et al., 2017) Were assessed eutrophication in Lake Nakuru using Landsat, Nsubuga analyzed water quality in Lake Kyoga using MODIS, and (Nakkazi et al., 2024) Nakkazi monitored seasonal variations in Tanzanian waters. The effectiveness of remote sensing in water quality monitoring lies in its ability to estimate parameters like chlorophyll-a, turbidity, and total suspended solids (TSS) using tailored algorithms and spectral bands on Earth observation satellites such as Landsat and Sentinel (Nativi & Bigagli, 2009; Zhou et al., 2022). These methods help overcome limitations in sensor resolution and data availability, improving the accuracy of water quality assessments (Deng et al., 2024). Looking ahead, the deployment of high-resolution and hyperspectral sensors is expected to significantly enhance the spatial and spectral capabilities of remote sensing platforms, leading to more precise monitoring and management of aquatic ecosystems (Bannari et al., 2022).

5. Mapping Water Quality for Lake Victoria

5.1. Area of Study Description

Lake Victoria is the largest tropical lake and the second-largest freshwater lake globally by surface area (68,800 km²), (Figure 1) located in East Africa between latitudes 0°20'N to 3°00'S and longitudes 31°39'E to 34°53'E. It sits at an altitude of approximately 1134 - 1135 meters above sea level and is shared among Tanzania (49% - 51%), Uganda (43% - 45%), and Kenya (6%) (Taabu-Munyaho et al., 2013; Simiyu et al., 2022). The lake has an average depth of 40 meters, with a max-

imum depth of up to 84 - 90 meters in the northeastern section. Its catchment area spans between 194,000 km² and 258,700 km², extending into Rwanda and Burundi (Odada et al., 2009; Cavalli et al., 2009). It forms the main reservoir of the Nile River system, playing a vital hydrological and economic role in the region. Lake Victoria supports the livelihoods of over 42 million people, providing water, food, and employment, especially through fishing, which yields approximately 1 million tons of fish annually and sustains more than 5 million people (Nalumenya et al., 2024; Outa et al., 2020; Nyamweya et al., 2023). Rainfall in the lake basin is bimodal, with “long rains” from March to May (MAM) and “short rains” from October to December (OND), influenced by zonal winds and intertropical convergence zones (Nicholson et al., 2021). Rainfall ranges between 900 - 2600 mm/year, while evaporation ranges from 1100 - 2400 mm/year. Despite its importance, Lake Victoria faces serious environmental threats from anthropogenic activities such as pollution, deforestation, eutrophication, urbanization, and climate change, which degrade its water quality (Mchau et al., 2019). Parameters such as Chlorophyll-a (Chl-a) and turbidity are used to monitor these impacts, with Chl-a serving as an indicator of phyto-plankton biomass and eutrophication (Gidudu et al., 2021), (Thiemann & Kaufmann, 2000; Koponen et al., 2002). The Lake Victoria Basin is one of the most densely populated regions in the world, with over 300 people/km² and an annual population growth rate of 3.5% (Odada et al., 2009). The lake’s extensive and transboundary nature makes it critical to maintain sustainable management and robust monitoring programs (Nassali et al., 2020).

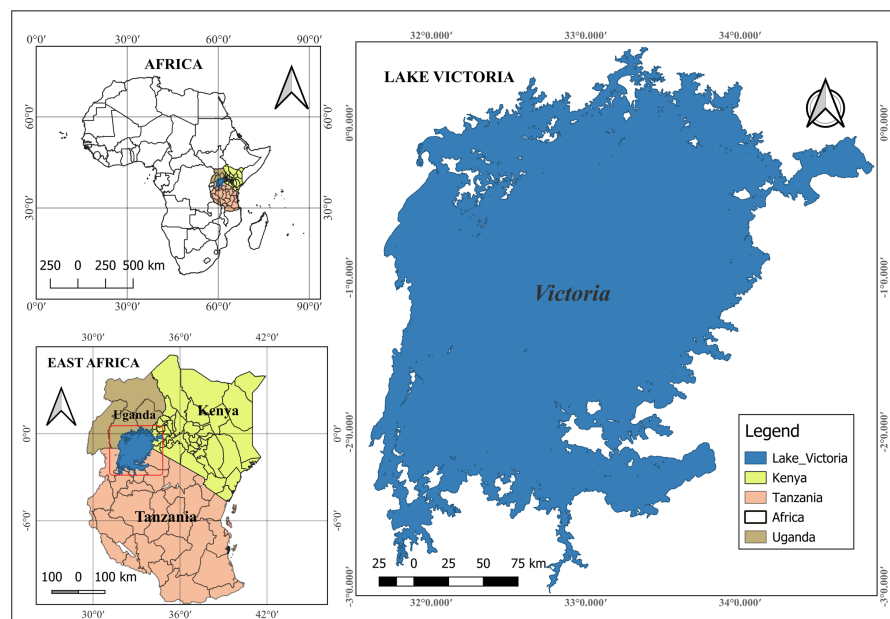


Figure 1. Study area map of Lake Victoria.

5.2. Data Sources and Collection

The primary data sources used was Landsat imageries as outlines in (Table 2). The study adopted an integrated remote sensing approach to monitor and map

water quality parameters of Lake Victoria, emphasizing the lake's ecological and economic significance and the need for sustainable environmental management. The key technologies and data tools used included Google Earth Engine (GEE), QGIS, and Jupyter Notebook, which collectively enabled efficient image processing, visualization, and statistical analysis. Landsat satellite imagery—specifically Landsat Collection 2 Tier 1 Level 2 Surface Reflectance and Surface Temperature Data—was the primary data source. Landsat's multispectral capabilities, including bands in the visible, NIR, and SWIR regions, made it ideal for water quality monitoring, band characteristics are well documented in the literature by Barsi (Barsi et al., 2014). The long-term data availability also allowed for temporal analysis to observe changes in water quality over time. Google Earth Engine (GEE) facilitated the processing of large volumes of imagery without the need for substantial local computing resources. Cloud masking, filtering, and index calculations were conducted automatically in GEE using JavaScript, while QGIS was used for post-processing tasks such as map generation and classification refinement. Python in Jupyter Notebook was utilized for advanced statistical analysis and machine learning operations.

Table 2. Landsat imagery characteristics used for mapping water quality in Lake Victoria.

No.	Image ID.	Time	Date	Spatial Resolution (M)	Cloud Cover %
1	LANDSAT/LT05/C02/T1_TOA	07:38:27	20/08/2010 (Friday)	30	Less than 10
2	LANDSAT/LE07/C02/T1_L2	07:32:17	10/03/2005 (Thursday)	30	Less than 10
3	LANDSAT/LC08/C02/T1_L2	08:48:59	16/11/2013 (Saturday)	30	Less than 20
4	LANDSAT/LC08/C02/T1_L2	08:49:24	25/02/2018 (Sunday)	30	Less than 8
5	LANDSAT/LC09/C02/T1_L2	07:49:44	14/11/2023 (Tuesday)	30	Less than 8

Source: Google Earth Engine catalogue.

5.3. Procedure for Mapping Water Quality for Lake Victoria

The study utilized Landsat imagery from five distinct years—2005, 2010, 2013, 2018, and 2023—acquired from the Google Earth Engine (GEE) cloud platform (see **Figure 2**). Simple JavaScript scripts were used within GEE to access and filter the images based on cloud cover, acquisition dates, and the geographic extent of Lake Victoria. The filtered images were then exported to Google Drive and later downloaded to local computer storage for further processing and analysis. In the subsequent steps, the acquired Landsat imagery was integrated into the QGIS interface for analysis. Quantum GIS (QGIS), (QGIS, 2025). A free and open-source cross-platform GIS software, was employed to map water quality in Lake Victoria using satellite imagery (raster datasets). Jupyter Notebook, (Python-based) was used in the project as a powerful tool for spatial data analysis, visualization, automation, and reproducible research. It provided an interactive environment for writing and executing Python code, visualizing geospatial data, and

documenting the workflow in a single, shareable format. In this study, both QGIS and Jupyter Notebook were utilized at various stages of the analysis. The Water Pollution Index (WPI) classification was computed using the Raster Calculator tool in both QGIS and Jupyter Notebook. For the qualitative accuracy assessment, sample points were generated using a passive-random sampling method in Google Earth Pro. These sample points were then overlaid onto the classified WPI raster layers, and WPI values were extracted using QGIS's raster extraction tools.

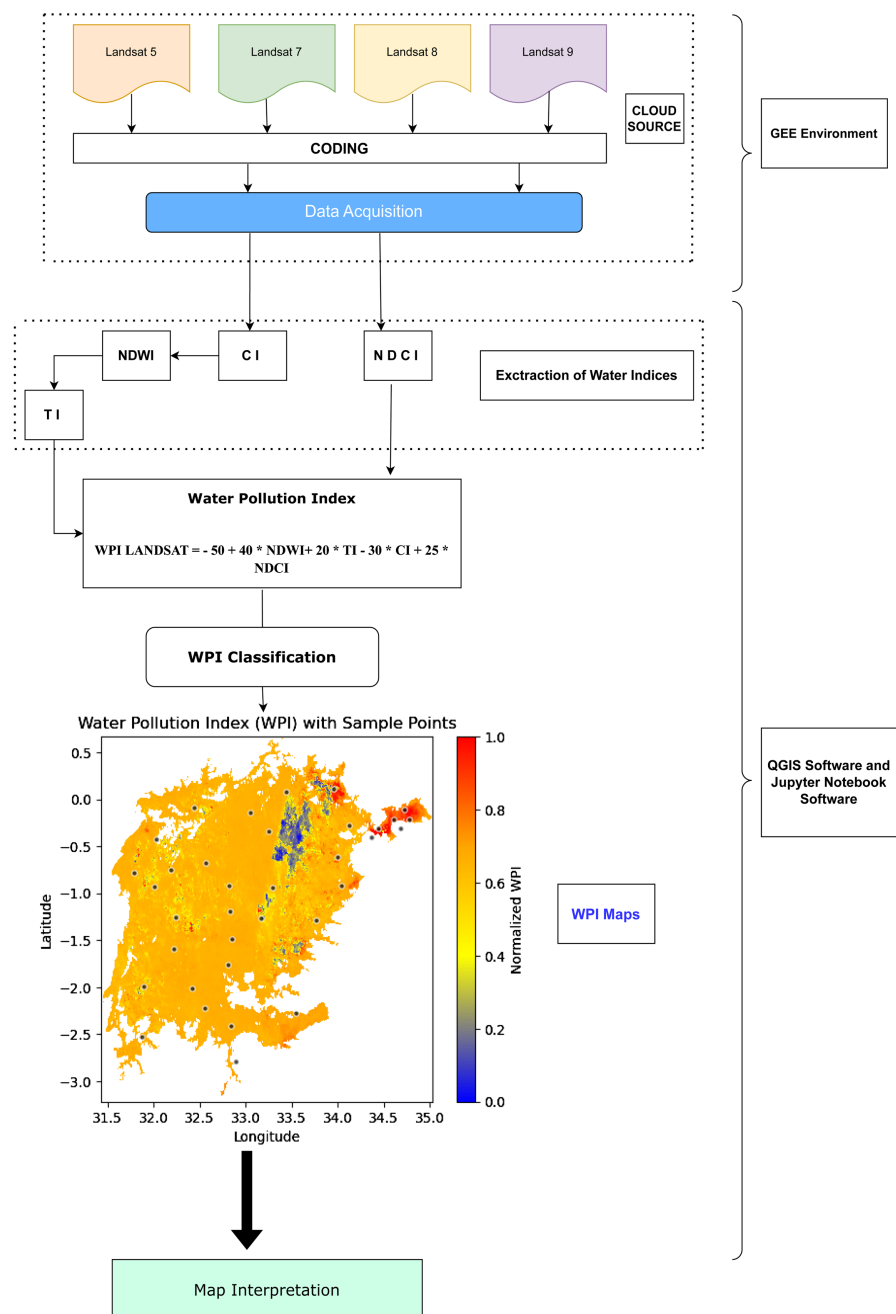


Figure 2. A systematic flowchart describing the processes taken in mapping water quality in Lake Victoria from Landsat imagery acquisition, processing, extraction of water indices, and computation of water pollution index (WPI) and visualization of water pollution maps.

To align with the classification chart adopted in the study, the WPI rasters were subsequently reclassified. A qualitative accuracy assessment was conducted at each sampling station, and insights were derived from the extracted WPI values. This systematic approach enabled a thorough analysis of water quality dynamics in Lake Victoria, leading to meaningful conclusions based on both the satellite-derived classifications and ground-reference data.

5.3.1. Sampling Data

The data used for the qualitative accuracy assessment were sampled from various locations across Lake Victoria using a passive quasi-random sampling technique.

5.3.2. Extraction of Water Indices

This was done by the use of QGIS raster calculator. The following vegetation indices were extracted.

- 1) Normalized Difference Water Index (NDWI) (Markogianni et al., 2020).

This function calculates NDWI using the Green and Near Infrared (NIR) bands: Equation 3.1:

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$

- 2) Chlorophyll Index (CI) (Singh et al., 2024).

This function calculates the Chlorophyll Index using the Green and Red bands: Equation 3.2:

$$\text{CI} = \text{Green} / \text{Red}$$

- 3) Turbidity Index (TI) (Mishra & Mishra, 2012).

This function calculates the Turbidity Index using the Red and NIR bands: Equation 3.3:

$$\text{TI} = \text{Red} / \text{NIR}$$

- 4) Normalized Difference Chlorophyll Index (NDCI) (Rawat et al., 2023).

This function calculates NDCI using the Red Edge and Red bands: Equation 3.4:

$$\text{NDCI} = (\text{RedEdge} - \text{Red}) / (\text{RedEdge} + \text{Red})$$

Equation 3.5: Water Pollution Index (WPI) Calculation

$$\text{WPI}(\text{LANDSAT}) = 50 + 40 \times \text{NDWI} + 20 \times \text{TI} - 30 \times \text{CI} + 25 \times \text{NDCI}$$





The weightings assigned to the Normalized Difference Water Index (NDWI), Turbidity Index (TI), Chlorophyll Index (CI), and Normalized Difference Chlorophyll Index (NDCI) in the Water Pollution Index (WPI) equation ($\text{WPI} = 50 + 40 \times \text{NDWI} + 20 \times \text{TI} - 30 \times \text{CI} + 25 \times \text{NDCI}$) were determined based on their relative contributions to water quality assessment, as informed by established literature (Liu et al., 2011; Gholizadeh & Porhamidi, 2020), the NDWI, with the highest positive weight of 40, is prioritized due to its robust ability to delineate water bodies and detect changes in water content, making it a critical indicator of overall water presence and quality. The TI, weighted at 20, reflects the influence

of suspended particles on water clarity, a key factor in pollution assessment, though less dominant than NDWI. The CI, assigned a negative weight of -30 , accounts for the inverse relationship between chlorophyll concentration and water quality, as higher chlorophyll levels often indicate eutrophication and algal blooms, which degrade water quality. The NDCI, with a positive weight of 25 , complements CI by capturing subtle variations in chlorophyll content using the red-edge band, enhancing the detection of phytoplankton dynamics. The base constant of 50 ensures the WPI remains within a practical range for interpretation. These weightings were calibrated to balance the sensitivity of each index to water pollution parameters, aligning with empirical findings from the referenced studies and the specific radiometric properties of LANDSAT imagery (Feng et al., 2023). Negative WPI values in remote sensing-based water quality assessments result from the weighted combination of multiple spectral indices—such as NDWI, TI, CI, and NDCI—in which pollutant indicators like chlorophyll-a concentration and turbidity often exert stronger influence than clarity indicators. This leads to a net negative output, particularly in highly polluted waters where elevated chlorophyll (via CI or NDCI) or sediment loads dominate the reflectance signal. However, negative values are not inherently invalid; they simply indicate the relative pollution severity within the index's mathematical structure. To transform these raw values into interpretable pollution classes, this classification facilitates spatial and temporal comparison of water quality and enhances the utility of satellite-derived indices for environmental monitoring and policy-making (Guo et al., 2017).

5.3.3. WPI Classification and Visualization

After the WPI was computed for every Landsat imagery used, they were reclassified as shown in **Table 3**.

Table 3. Water Pollution Index classification scheme.

NO.	Class	Symbology
1	Good	
2	Medium	
3	Unhealthy	
4	Very unhealthy	

The sample points were overlaid on each classified WPI map to provide spatial reference and assist in interpreting the distribution of pollution levels across Lake Victoria. This overlay helped visualize how specific sampling locations correspond to varying levels of water quality, thereby enhancing both the qualitative and quantitative assessment of the WPI data. By comparing the sample points against the classified colors (blue, yellow, orange, red), researchers could better understand how pollution is spatially distributed and how specific regions correlate with particular pollution intensities. Following the overlay, WPI values were extracted from the

classified raster images using the bilinear interpolation method, which estimates the value at each point by averaging the values of surrounding pixels. This method ensures a more accurate representation of pixel values, especially in heterogeneous regions. The extraction process was performed using the raster-to-point tool in Quantum GIS (QGIS), allowing for a smooth conversion of raster data into discrete point data aligned with the sample locations. The extracted values were then compiled and saved as CSV files for further statistical analysis and tabular representation, enabling easier interpretation, cross-comparison, and reporting.

6. Results

6.1. Water Pollution Information from Landsat 5 Imagery for 2010

The 2010 Water Pollution Index (WPI) analysis of Lake Victoria using Landsat 5 imagery assessed water quality at 35 sampling points, classifying them into four categories: Good (Blue), Medium (Yellow), Unhealthy (Orange), and Very Unhealthy (Red). The WPI was computed using the formula

$$\text{WPI} = 50 + 40 \times \text{NDWI} + 20 \times \text{TI} - 30 \times \text{CI} + 25 \times \text{NDCI}$$
, which portrays key remote sensing indices to estimate pollution levels. Only four points—3 (1.12), 14 (1.63), 18 (4.15), and 25 (3.29)—were classified as “Good,” suggesting clean, mid-lake waters with minimal anthropogenic impact. These areas are marked in blue on the WPI map and represent potential reference zones for future conservation and monitoring efforts. Most sample points fell into the “Unhealthy” and “Very Unhealthy” categories, indicating widespread water degradation. “Unhealthy” WPI values ranged from -7 to -19.86 , while “Very Unhealthy” points showed extreme values such as -30.73 , -31.93 , and as low as -74.54 at Point 21, the most contaminated site. These highly polluted zones were concentrated around major urban centers: Kisumu, Homa Bay, Migori, and Kisii in Kenya; Kampala and Entebbe in Uganda; and Mwanza and Musoma in Tanzania. Kisumu stood out due to its role as a port city with poor wastewater management, leading to nutrient and sediment accumulation in the Winam Gulf. Similarly, Kampala’s untreated effluent enters the lake via the Nakivubo and Katonga rivers, while Mwanza contributes industrial waste through the Mirongo River. Pollution levels were highest along the northern, northeastern, and southern shores, reflecting dense population, urban development, and industrial discharge, while the central lake exhibited relatively lower WPI values due to dilution and fewer direct pollution sources. The study demonstrates a clear correlation between urbanization and declining water quality, with spatial clustering pointing to both point and diffuse pollution sources. It highlights the utility of satellite-based remote sensing for large-scale water quality monitoring and calls for urgent policy action, cross-border cooperation, and improved watershed management through regional frameworks like the Lake Victoria Basin Commission and the East African Community.

Ref: **Table A1** (annexed).

Figure 3 shows the water pollution categorized in WPI values as highlighted in **Table 3**. The result is from the extraction of WPI values from the Landsat 5 scene

for Lake Victoria in the year 2010.

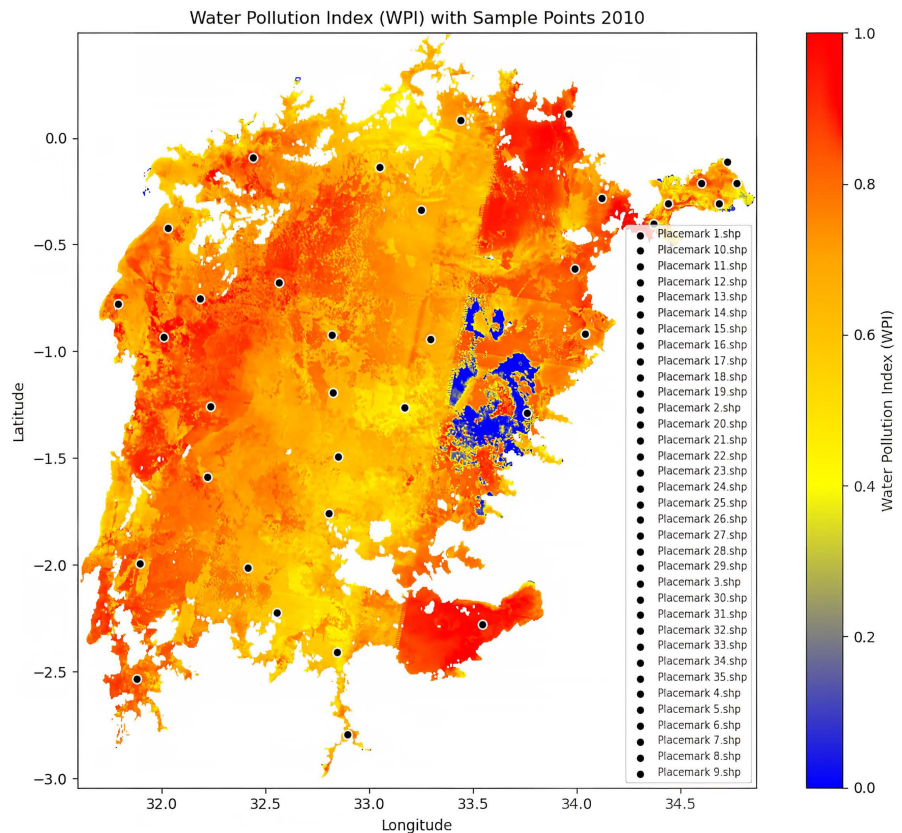


Figure 3. A map showing the Water pollution (WPI) categorization in 2010 for Landsat 5 sample imagery.

6.2. Water Pollution Information from Landsat Imagery

Table 3 presents the classification system used for interpreting the Water Pollution Index (WPI) in the context of water quality assessment. It categorizes pollution levels into four distinct classes: Good, Medium, Unhealthy, and Very Unhealthy, each associated with a specific numerical code from 1 to 4. These classes help translate quantitative WPI values into qualitative assessments of ecological health. The “Good” category (No. 1) signifies areas with low or negligible pollution, indicating favorable water conditions, while the “Medium” class (No. 2) denotes zones experiencing moderate environmental stress, often due to limited human activity. Each class is color-coded to enhance visual interpretation on thematic maps: blue for Good, yellow for Medium, orange for Unhealthy, and red for Very Unhealthy. The “Unhealthy” (No. 3) and “Very Unhealthy” (No. 4) categories reflect increasing levels of pollution, with red zones being the most ecologically degraded and in need of urgent attention. This symbology enables an intuitive spatial analysis of water quality conditions, helping identify critical hotspots, monitor trends over time, and guide decision-making for lake management and environmental protection efforts.

6.3. Water Pollution Information from Landsat 7 Imagery for 2005

In 2005, Landsat 7 satellite imagery was used to assess water quality across Lake Victoria through the Water Pollution Index (WPI), derived from a combination of remote sensing indices—NDWI, Turbidity Index, Chlorophyll Index (CI), and Normalized Difference Chlorophyll Index (NDCI). WPI values for 35 geospatial sample points ranged from -11.76 to -46.91 and were categorized into four pollution levels: Blue (Good), Yellow (Moderate), Orange (Unhealthy), and Red (Very Unhealthy). The cleanest waters were found in areas like Placemark 14 (-11.76), Placemark 5 (-14.14), and Placemark 16 (-17.32), suggesting low human impact and minimal nutrient inflow. These zones, primarily located in relatively undisturbed parts of the lake, reflect better ecological conditions, possibly due to limited sediment runoff and fewer anthropogenic pressures. Conversely, a significant number of sample points showed unhealthy to very unhealthy pollution levels, especially in the orange and red categories. The most degraded areas included Placemark 2 (-46.91), 27 (-46.03), and 35 (-43.67), highlighting zones suffering from chronic pollution, likely due to untreated wastewater, algal blooms, and nutrient overloading. These critical pollution hotspots were often found near major urban and industrial centers. On the Kenyan side, Kisumu, Homa Bay, and Migori were strongly associated with high WPI values due to urban wastewater, industrial discharge, and agricultural runoff—particularly affecting Winam Gulf. In Uganda, cities such as Kampala, Entebbe, and Jinja heavily polluted surrounding lake areas like Murchison Bay. Tanzanian towns like Mwanza and Musoma also contributed to the lake's pollution, although some southern zones (e.g., Bunda, Kisesa) showed moderate to cleaner conditions, likely benefiting from lower population density or natural buffers. Overall, the WPI imagery revealed that a majority of Lake Victoria's sampled sites were in a state of moderate to severe pollution, with only a handful exhibiting relatively good water quality. The spatial trend indicated that pollution was most intense along the northern and northeastern shores—particularly around urban hubs in Uganda and western Kenya—while southern Tanzanian zones were comparatively less impacted. This analysis underscores the urgent need for cross-border collaboration in watershed management, investment in sewage treatment infrastructure, and the integration of satellite monitoring for early detection and long-term tracking. Such efforts are critical for mitigating further environmental degradation and guiding sustainable management policies for the Lake Victoria basin. **Figure 4** shows the distribution of water pollution over Lake Victoria in 2005. Landsat 7 imagery was used as the primary data.

6.4. Water Pollution Information from Landsat 8 Imagery for 2013

The 2013 Landsat 8-based Water Pollution Index (WPI) imagery analysis of Lake Victoria revealed widespread water quality deterioration, with WPI values ranging from -8.66 to -330.64 across 35 sample points. The WPI formula—
$$\text{WPI} = 50 + 40 \times \text{NDWI} + 20 \times \text{TI} - 30 \times \text{CI} + 25 \times \text{NDCI}$$
—integrates turbidity,

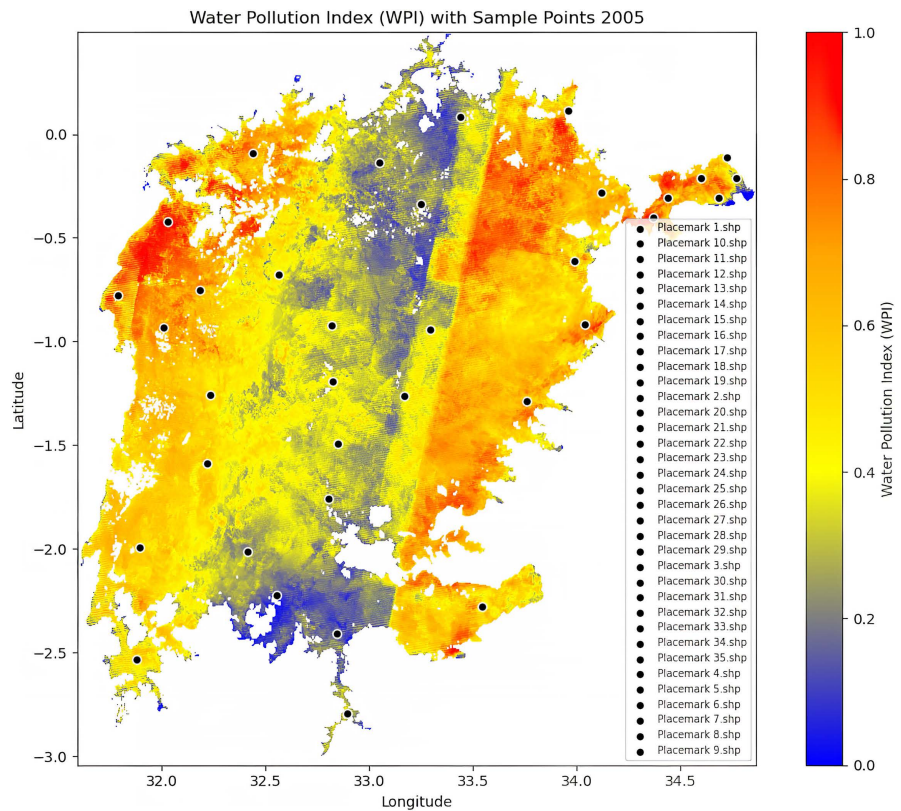


Figure 4. A map showing the Water pollution (WPI) categorization in 2005 for Landsat 7 sample imagery.

chlorophyll levels, water availability, and algae content. While the numerical values fell outside a normalized scale, visual classification into Blue (Good), Yellow (Moderate), Orange (Unhealthy), and Red (Very Unhealthy) allowed qualitative interpretation. The highest water quality was observed at Point 6 (−8.66) and Point 24 (−30.53), suggesting isolated areas of better natural circulation or less anthropogenic interference. In contrast, Points 29 (−330.64) and Point 34 (−259.97) presented as computational outliers but visually still indicated poor water conditions. A geographic breakdown of the points shows notable pollution near major towns. In Kenya, Kisumu and the Winam Gulf displayed alarmingly low WPI values (−44.12 to −40.70 at Points 2 - 5), likely due to urban runoff and industrial discharges. Points 10 to 14 in the central north (e.g., near Homa Bay and Kendu Bay) showed WPI values from −65.02 to −57.99, reflecting consistently poor water quality possibly caused by sedimentation and eutrophication. Points in the southern region near Mwanza, Tanzania, also showed significant degradation, particularly Point 30 (−127.06) and Point 34 (−259.97), highlighting intense pollution from untreated waste, agriculture, and mining. A spatial interpolation map further categorized the lake's WPI into four bands: Blue (0.00 - 0.25), Yellow (0.26 - 0.50), Orange (0.51 - 0.75), and Red (0.76 - 1.00), based on normalized pollution severity. Of the 35 locations, 8 fell in the Blue (Good) zone, mostly in the northwest, and 11 in Yellow, mostly central. The southern basin had 9 Orange-class

points, while the southeast and southwest had 7 Red-class sites, confirming pollution hotspots near urban centers and agricultural zones. This gradient aligned with land use, urbanization, and proximity to effluent discharge points. Country-level urban analysis confirms that Kisumu (Kenya), Jinja and Kampala (Uganda), and Mwanza (Tanzania) are major contributors to the lake's deteriorating quality. Kenya's Sondu and Nyando rivers, and Uganda's Nakivubo Channel draining into Murchison Bay, carry industrial and domestic effluents directly into the lake. Tanzania's southern coast, particularly around Magu, Bunda, and Musoma, correlates with high WPI due to runoff from agriculture and livestock. While some areas like Bukoba and Entebbe show intermediate WPI, most areas near major urban centers were classified in orange or red zones. The 2013 WPI analysis from satellite data provides essential insight into Lake Victoria's transboundary pollution crisis as shown in **Figure 5**. The widespread degradation suggests that environmental management cannot be country-specific but rather demands regional cooperation among Kenya, Uganda, and Tanzania. The East African Community (EAC) and Lake Victoria Basin Commission (LVBC) must lead in enforcing standardized monitoring, pollution control, and conservation protocols. Despite issues with data normalization, the study confirms remote sensing's effectiveness in identifying pollution zones and guiding interventions aimed at restoring the lake's ecological health.

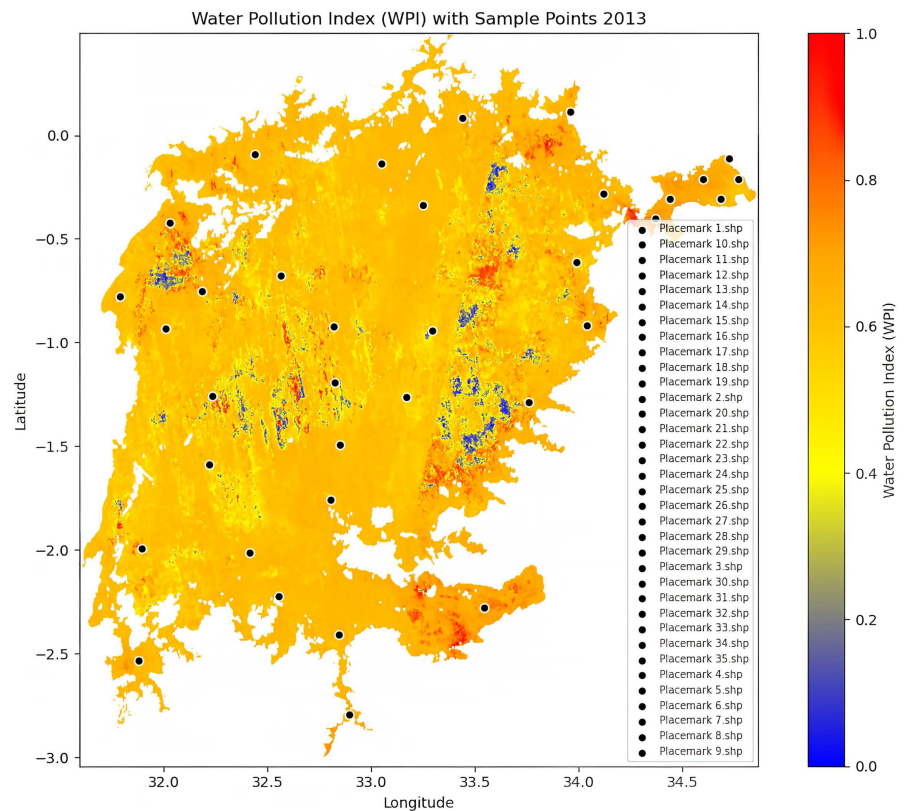


Figure 5. A map showing the Water pollution (WPI) categorization in 2013 for Landsat 8 sample imagery.

6.5. Water Pollution Information from Landsat 8 Imagery for 2018

The analysis of the Water Pollution Index (WPI) from Landsat 8 imagery for 2018 across 35 sites on Lake Victoria reveals stark differences in water quality. The WPI, calculated using a formula integrating NDWI, TI, CI, and NDCI indices, categorized water quality into four levels: Good (Blue), Medium (Yellow), Unhealthy (Orange), and Very Unhealthy (Red). Only two points, 14 and 24, fell under the Good category, reflecting low turbidity and chlorophyll with minimal anthropogenic influence. Notably, no sites were classified as Medium, suggesting a sharp divide between clean and polluted areas. This absence of transitional zones implies that once pollution begins, degradation accelerates quickly. Eight sites fell within the Unhealthy (Orange) range, mostly near river mouths, suburban zones, or agricultural regions. These areas exhibit moderate pollution, suggesting early warning signs where corrective actions could still be effective. The pollution here, although concerning, hasn't overwhelmed the lake's resilience completely. Sediment and nutrient runoff are likely the main contributors, yet chlorophyll and turbidity levels remain relatively low. Such regions are crucial targets for preventive interventions before they shift irreversibly into the Very Unhealthy category. A total of 25 sites were classified as Very Unhealthy (Red), signaling extreme pollution and environmental stress. These sites likely suffer from hypereutrophic conditions, marked by algal blooms, anoxic waters, and fish kills. Points like 12 and 35 recorded the lowest WPI values, suggesting possible ecological dead zones with stagnation, high nutrient concentration, and low biodiversity. These critically degraded zones often align with urban, industrial, or river inflow areas, such as Kisumu, Homa Bay, and major river outlets like Nyando and Nzoia, where untreated waste and runoff are prevalent. The spatial distribution of WPI data emphasizes Lake Victoria's overall environmental deterioration, with 94% of the sampled sites falling into Unhealthy or Very Unhealthy categories. This severe pollution is driven largely by human activities, including untreated sewage, agricultural runoff, and industrial discharges. The findings stress the need for urgent intervention through catchment management, wetland restoration, wastewater treatment enforcement, and satellite-based monitoring. While a few clean offshore areas still exist, they are exceptions and demonstrate that ecological recovery is possible if proper controls are implemented. Lastly, the variation in pollution aligns with land use and urbanization patterns around the lake. Major cities like Kisumu, Kampala, Jinja, Mwanza, and Musoma, along with smaller growing towns, are key pollution sources. These areas often lack proper waste infrastructure, and wetlands—natural filters for nutrients—have been degraded. The bimodal WPI distribution (extremely good or very poor) indicates either abrupt environmental collapse or ineffective regulation. A comprehensive lake governance strategy, harmonized across the three countries, supported by satellite tools and community involvement, is essential for reversing the pollution trend and safeguarding Lake Victoria's future as shown in **Figure 6**.

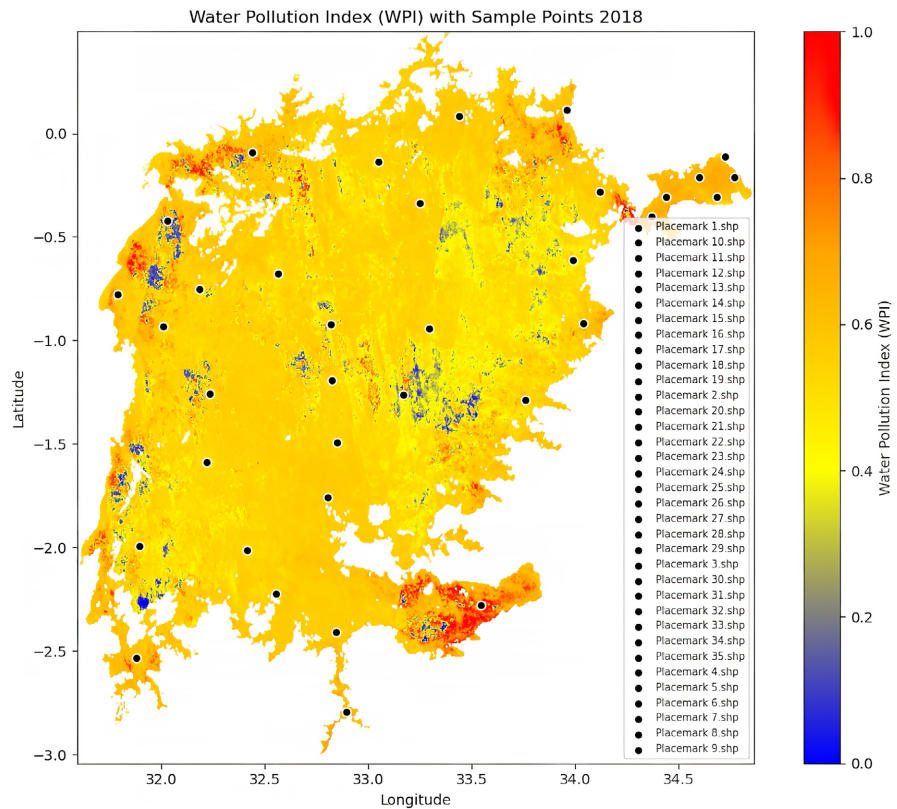


Figure 6. A map showing the Water pollution (WPI) categorization in 2018 for Landsat 8 sample imagery.

6.6. Water Pollution Information from Landsat 9 Imagery for 2023

The 2023 Water Pollution Index (WPI) assessment of Lake Victoria, derived from Landsat 9 satellite imagery using remote sensing indices (NDWI, TI, CI, and NDCI), provides an in-depth spatial overview of water quality across 35 strategically distributed sampling points. The WPI values ranged widely from +69.79 (indicating good water quality) to -130.17 (indicating severe pollution), and were classified into four qualitative categories: Blue (Good), Yellow (Medium), Orange (Unhealthy), and Red (Very Unhealthy). These categories revealed a stark picture: only one site (Point 5) exhibited good water quality, while 25 of the 35 sites were classified as Very Unhealthy. This distribution demonstrates a widespread degradation of water quality, especially in near shore and central regions of the lake, commonly adjacent to urban and river inflow zones. The only site categorized as Good (Blue), Point 5, is located offshore in a relatively isolated, part of the lake. Its WPI value of +69.79 suggests minimal pollutant influence, likely due to its distance from land-based pollution sources and deeper water that promotes greater dilution. Moderately polluted zones were identified at Points 3 and 4, with WPI values of 17.67 and 41.92 respectively, placing them in the Medium (Yellow) category. These zones may benefit from hydrodynamic mixing and less direct discharge of pollutants, reflecting limited anthropogenic interference. In contrast, seven sampling locations (Points 2, 9, 23, 24, 25, 27, and 32) were classified as

Unhealthy (Orange), primarily located in the western and southern sectors of the lake. These areas likely suffer from diffuse sources of pollution such as agricultural runoff, poorly managed domestic waste, and sediment transport. The Red category, representing Very Unhealthy conditions, dominates the WPI classification map. Sites such as Point 11 (−130.17) and Point 20 (−91.66) were identified as the most polluted, suggesting hotspots of eutrophication and potential harmful algal blooms. Several points within the central and western basins, particularly Points 12 through 19, were significantly affected, with WPI values ranging from −61.42 to −85.85. These locations are situated near the mouths of major rivers like the Sio and Nzoia, which transport high sediment and nutrient loads from upstream land-use activities, including farming and deforestation. Similar high-pollution conditions were also recorded in southern sites (e.g., Points 28, 29, 30, and 34), which may reflect the compounded effects of poor catchment management, livestock rearing, and increased population pressure on the surrounding environment. From a geographical perspective, the pollution is widely distributed across the lake's international borders. In Kenya, urban centers such as Kisumu, Homa Bay, Mbita, Migori, and Kendu Bay exhibit strong pollution signatures, largely due to domestic sewage, industrial effluent, and nutrient-laden runoff from agricultural fields. River inflows from the Nyando and Sondu rivers intensify this condition. On the Ugandan side, Jinja, Kampala (via the Nakivubo Channel), and Entebbe contribute to heavy nutrient and waste loads entering the lake, particularly into Murchison Bay. Rapid peri-urban expansion in Mukono and Masaka also exacerbates non-point pollution. In Tanzania, cities like Mwanza, Musoma, and Bukoba contribute both industrial waste and agricultural runoff, with particularly high pollution observed in the Ilemela and Nyamagana districts. Southern zones, such as Magu and Bunda, also exhibit Very Unhealthy WPI values due to intensive farming and livestock activities. In summary, the WPI classification from Landsat 9 reveals a grim status for Lake Victoria's water quality, **Figure 7** with more than 70% of sampled sites falling under the Very Unhealthy category. This highlights the urgent need for coordinated regional interventions, especially through institutions such as the Lake Victoria Basin Commission (LVBC) and the East African Community (EAC). Efforts must include improved watershed management, enforcement of pollution control regulations, promotion of best practices in agriculture, and implementation of real-time water quality monitoring systems. Although isolated areas such as Point 5 indicate the lake's resilience, they are increasingly rare and shrinking. The remote sensing-based WPI tool demonstrates its value in capturing the lake's spatial pollution dynamics and provides a scientific foundation for policy decisions aimed at reversing the lake's ongoing ecological degradation.

7. Practical Implications and Limitations of the Study

This study highlights the transformative role of remote sensing technologies in enhancing water quality monitoring, especially in vast and dynamic freshwater

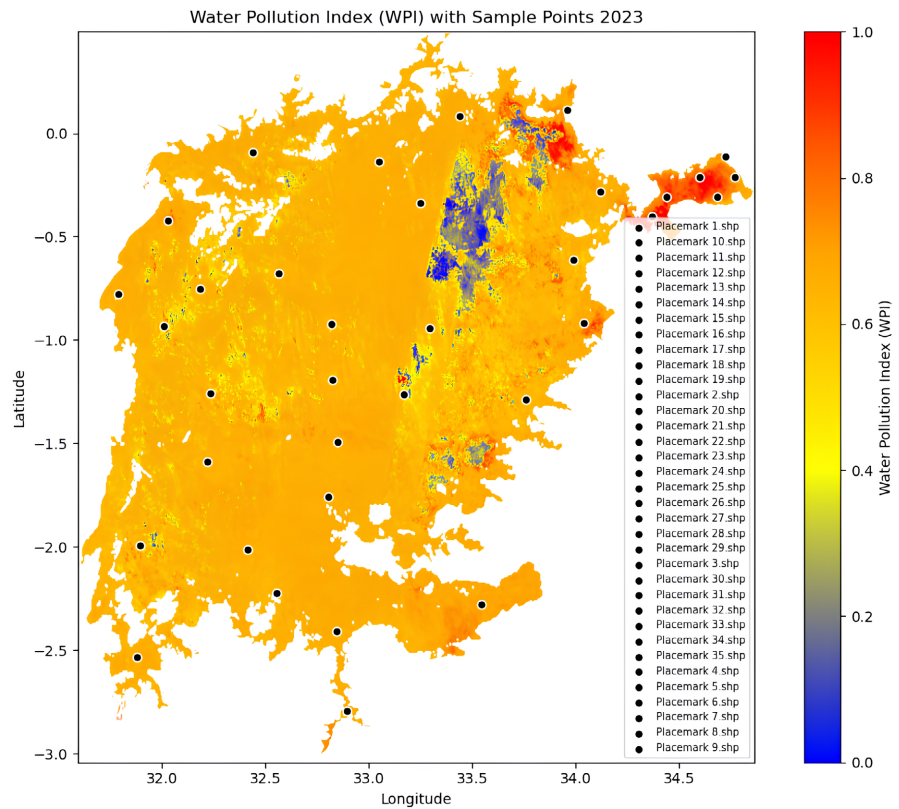


Figure 7. A map showing the Water pollution (WPI) categorization in 2023 for Landsat 9 sample imagery.

systems like Lake Victoria. By leveraging satellite data from the Landsat missions and processing it using platforms such as Google Earth Engine (GEE) and Python, the study demonstrates that timely, consistent, and cost-effective water quality assessments are achievable even in resource-constrained environments. The outputs—comprising Water Pollution Index (WPI) maps and pollution trend analyses—can serve as crucial tools for policymakers, environmental agencies such as NEMA, and regional bodies like the Lake Victoria Basin Commission (LVBC) to make informed decisions regarding pollution control and sustainable water resource management. The study also provides a practical framework that can be adapted and scaled to other water bodies across Africa and globally. The use of spectral indices like NDWI, SSI, and TI as proxies for chlorophyll-a, suspended sediments, and turbidity offers a replicable method for continuous monitoring. This is particularly valuable in regions where conventional monitoring infrastructure is sparse or outdated. Furthermore, the integration of open-source platforms ensures that the methodology remains accessible to institutions and researchers in developing countries, thereby promoting greater regional capacity for environmental monitoring and data-driven governance. However, the study faced certain limitations, particularly regarding spatial and temporal resolution. The 30-meter spatial resolution of Landsat imagery, while adequate for large-scale trends, may not capture fine-scale pollution sources such as near-shore discharges or localized

industrial effluents. Similarly, the 16-day revisit cycle may overlook short-term pollution events, such as those triggered by storms or sewage overflows. Another limitation stems from the reliance on remotely sensed proxies, which, while informative, are not direct measurements and may be influenced by atmospheric conditions or sensor limitations. These challenges highlight the need for hybrid systems that combine satellite data with in-situ measurements and citizen science contributions for improved water quality assessment.

8. Conclusion

The study successfully demonstrates that remote sensing, when coupled with geospatial analytics, offers a viable alternative to traditional water quality monitoring methods for Lake Victoria. Through the calculation of spectral indices and development of a Water Pollution Index (WPI), it was possible to visualize and quantify pollution levels across space and time. The results revealed a clear pattern of degradation, particularly in urban and industrialized zones, such as Kisumu and Mwanza, where elevated levels of turbidity and chlorophyll-a were consistently detected. These findings not only affirm the value of Earth observation technologies but also underscore the pressing environmental challenges facing Lake Victoria. A key contribution of the research is the development of a reproducible methodology that supports real-time and large-area water quality monitoring. The integration of cloud-based tools (GEE), programming environments (Python), and GIS software (QGIS) creates a powerful workflow that can be adapted by environmental agencies, academic researchers, and development organizations. By shifting from reactive to proactive environmental monitoring, stakeholders can implement timely interventions, track policy impacts, and promote sustainable practices among local communities and industries. Such geospatial intelligence is essential for achieving Sustainable Development Goals, particularly SDG 6 on clean water and sanitation. In conclusion, this study provides compelling evidence that satellite-based remote sensing is not only a complementary tool but a necessary asset in modern water resource management. As climate change and population growth continue to exert pressure on freshwater ecosystems, embracing innovative technologies will be essential for safeguarding environmental and public health. The adoption of such integrative monitoring systems, combined with robust policy frameworks and regional cooperation, offers a pathway to restore and preserve the ecological integrity of Lake Victoria and similar water bodies across the globe.

Acknowledgements

The authors are grateful to the Department of Geomatic Engineering and Geospatial Information Systems at JKUAT for their technical support and enabling research environment. Special thanks go to the Google Earth Engine, Python programming language, and the U.S. Geological Survey (USGS) platform for providing access to high-quality satellite data, cloud computing resources, and open-

source tools that were instrumental in data analysis, image processing, and computation of indices used in this study. I deeply appreciate my parents, Joseph Nyongesa and Berita Sing'oro, whose financial and moral support throughout the master's. Lastly, I sincerely thank my mentors, siblings, and friends for their unwavering encouragement and support, which greatly contributed to the successful completion of this research.

Author Contribution

Gideon Wafula Simiyu: conceptualization, methodology, software, data curation, writing, original draft preparation, visualization, investigation. Josphat Mwatelah: conceptualization and design of the study, supervision of the research, reviewing, writing and editing the manuscript, granting final approval of the version to be submitted.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- Ali, M., Ali, T., Gawai, R., Dronjak, L., & Elaksher, A. (2024). The Analysis of Land Use and Climate Change Impacts on Lake Victoria Basin Using Multi-Source Remote Sensing Data and Google Earth Engine (GEE). *Remote Sensing*, *16*, Article 4810. <https://doi.org/10.3390/rs16244810>
- Anatolia S.M. Exposto, L., Nahak Lino, M., A.C. Quim, J., Juvi Goncalves, M., & Pereira Vicente, H. (2021). Efforts to Improve Clean Water Quality to Support Community Health. *KESANS: International Journal of Health and Science*, *1*, 236-251. <https://doi.org/10.54543/kesans.v1i3.24>
- Attey-Yeboah, P., Afful, C., Yeboah, K., Korkpoe, C. H., Coker, E. S., Subramanian, R. et al. (2025). Utility of Low-Cost Sensor Measurement for Predicting Ambient Pm_{2.5} Concentrations: Evidence from a Monitoring Network in Accra, Ghana. *Environmental Science: Atmospheres*, *5*, 517-529. <https://doi.org/10.1039/d4ea00140k>
- Awange, J. L. (2021). *Lake Victoria Monitored from Space*. Springer. <https://doi.org/10.1007/978-3-030-60551-3>
- Awange, J. L., & Ong'ang'a, O. (2006). *Lake Victoria: Ecology, Resources, Environment*. Springer Berlin Heidelberg.
- Bannari, A., Ali, T. S., & Abahussain, A. (2022). The Capabilities of Sentinel-MSI (2A/2B) and Landsat-Oli (8/9) in Seagrass and Algae Species Differentiation Using Spectral Reflectance. *Ocean Science*, *18*, 361-388. <https://doi.org/10.5194/os-18-361-2022>
- Barsi, J., Lee, K., Kvaran, G., Markham, B., & Pedelty, J. (2014). The Spectral Response of the Landsat-8 Operational Land Imager. *Remote Sensing*, *6*, 10232-10251. <https://doi.org/10.3390/rs61010232>
- Bashir, I., Lone, F. A., Bhat, R. A., Mir, S. A., Dar, Z. A., & Dar, S. A. (2020). Concerns and Threats of Contamination on Aquatic Ecosystems. In K. Hakeem, R. Bhat, & H. Qadri (Eds.), *Bioremediation and Biotechnology* (1-26). Springer International Publishing. https://doi.org/10.1007/978-3-030-35691-0_1
- Batina, A., & Krtalić, A. (2024). Integrating Remote Sensing Methods for Monitoring Lake Water Quality: A Comprehensive Review. *Hydrology*, *11*, Article 92.

- <https://doi.org/10.3390/hydrology11070092>
- Beshiru, A., Isokpehi, N. A., Igbinsosa, I. H., Akinnibosun, O., Ogofure, A. G., & Igbinsosa, E. O. (2024). Extended-Spectrum Beta-Lactamase (ESBL)- and Non-ESBL Producing Escherichia Coli Surveillance in Surface Water Sources in Edo State, Nigeria: A Public Health Concern. *Scientific Reports*, 14, Article No. 21658. <https://doi.org/10.1038/s41598-024-72993-w>
- Brooks, B. W., Lazorchak, J. M., Howard, M. D. A., Johnson, M. V., Morton, S. L., Perkins, D. A. K. et al. (2016). Are Harmful Algal Blooms Becoming the Greatest Inland Water Quality Threat to Public Health and Aquatic Ecosystems? *Environmental Toxicology and Chemistry*, 35, 6-13. <https://doi.org/10.1002/etc.3220>
- Campos da Rocha, F. O., Martinez, S. T., Campos, V. P., da Rocha, G. O., & de Andrade, J. B. (2021). Microplastic Pollution in Southern Atlantic Marine Waters: Review of Current Trends, Sources, and Perspectives. *Science of The Total Environment*, 782, Article 146541. <https://doi.org/10.1016/j.scitotenv.2021.146541>
- Cavalli, R. M., Laneve, G., Fusilli, L., Pignatti, S., & Santini, F. (2009). Remote Sensing Water Observation for Supporting Lake Victoria Weed Management. *Journal of Environmental Management*, 90, 2199-2211. <https://doi.org/10.1016/j.jenvman.2007.07.036>
- Chow, R., Scheidegger, R., Doppler, T., Dietzel, A., Fenicia, F., & Stamm, C. (2020). A Review of Long-Term Pesticide Monitoring Studies to Assess Surface Water Quality Trends. *Water Research X*, 9, Article 100064. <https://doi.org/10.1016/j.wroa.2020.100064>
- Deng, Y., Zhang, Y., Pan, D., Yang, S. X., & Gharabaghi, B. (2024). Review of Recent Advances in Remote Sensing and Machine Learning Methods for Lake Water Quality Management. *Remote Sensing*, 16, Article 4196. <https://doi.org/10.3390/rs16224196>
- Drouillard, K. G., Campbell, L., Otieno, D., Achiya, J., Getabu, A., Mwamburi, J. et al. (2024). Increasing Mercury Bioaccumulation and Biomagnification Rates of Nile Perch (*Lates niloticus* L.) in Winam Gulf, Lake Victoria, Kenya. *Science of The Total Environment*, 916, Article 170059. <https://doi.org/10.1016/j.scitotenv.2024.170059>
- Dube, T., Mutanga, O., Seutloali, K., Adelabu, S., & Shoko, C. (2015). Water Quality Monitoring in Sub-Saharan African Lakes: A Review of Remote Sensing Applications. *African Journal of Aquatic Science*, 40, 1-7. <https://doi.org/10.2989/16085914.2015.1014994>
- Feng, Z., Xu, C., Zuo, Y., Luo, X., Wang, L., Chen, H. et al. (2023). Analysis of Water Quality Indexes and Their Relationships with Vegetation Using Self-Organizing Map and Geographically and Temporally Weighted Regression. *Environmental Research*, 216, Article 114587. <https://doi.org/10.1016/j.envres.2022.114587>
- Feyisa, G. L., Meilby, H., Fensholt, R., & Proud, S. R. (2014). Automated Water Extraction Index: A New Technique for Surface Water Mapping Using Landsat Imagery. *Remote Sensing of Environment*, 140, 23-35. <https://doi.org/10.1016/j.rse.2013.08.029>
- Fuss, G. (2019). *Turbidity Dynamics in Small Streams as a Key Component of Water Quality Management*. Doctoral Dissertation, University of British Columbia. <https://open.library.ubc.ca/collections/ubctheses/24/items/1.0376581>
- Gao, H., Wang, L., Jing, L., & Xu, J. (2016). An Effective Modified Water Extraction Method for Landsat-8 OLI Imagery of Mountainous Plateau Regions. *IOP Conference Series: Earth and Environmental Science*, 34, Article 012010. <https://doi.org/10.1088/1755-1315/34/1/012010>
- Gholizadeh, M., & Porhamidi, F. (2020). Health Assessment of Water Quality of Madarsoo River (Golestan Province) Using Multimetric Biological Index. *Journal of Environmental Studies*, 46, 375-390.
- Gidudu, A., Mpakiraba, Z., & Kalibbala, H. (2021). Exploring Modis Imagery in Monitor-

- ing Water Quality on Lake Victoria. *Journal of Great Lakes Research*, 47, 1086-1095.
- Gordon, H. R., & Wang, M. (1994). Retrieval of Water-Leaving Radiance and Aerosol Optical Thickness over the Oceans with Seawifs: A Preliminary Algorithm. *Applied Optics*, 33, 443-452. <https://doi.org/10.1364/ao.33.000443>
- Guo, Q., Pu, R., Li, J., & Cheng, J. (2017). A Weighted Normalized Difference Water Index for Water Extraction Using Landsat Imagery. *International Journal of Remote Sensing*, 38, 5430-5445. <https://doi.org/10.1080/01431161.2017.1341667>
- Haldar, K., Kujawa-Roeleveld, K., Hofstra, N., Datta, D. K., & Rijnaarts, H. (2022). Microbial Contamination in Surface Water and Potential Health Risks for Peri-Urban Farmers of the Bengal Delta. *International Journal of Hygiene and Environmental Health*, 244, Article 114002. <https://doi.org/10.1016/j.ijheh.2022.114002>
- Huang, C., Chen, Y., Zhang, S., & Wu, J. (2018). Detecting, Extracting, and Monitoring Surface Water from Space Using Optical Sensors: A Review. *Reviews of Geophysics*, 56, 333-360. <https://doi.org/10.1029/2018rg000598>
- Hung, D. T., Thi Cuc, V., Thi Bich Phuong, V., Thi Thanh Diu, D., Thi Huyen Trang, N., Phuong Thoa, N. et al. (2020). Evaluation of Drinking Water Quality in Schools in a District Area in Hanoi, Vietnam. *Environmental Health Insights*, 14, 1-8. <https://doi.org/10.1177/1178630220959672>
- Jiang, Y., Kong, J., Zhong, Y., Zhang, J., Zheng, Z., Wang, L. et al. (2024). The Optimal Method for Water Quality Parameters Retrieval of Urban River Based on Machine Learning Algorithms Using Remote Sensing Images. *International Journal of Remote Sensing*, 45, 7297-7317. <https://doi.org/10.1080/01431161.2023.2209918>
- Jonah, U. E., & Archibong, I. J. (2022). Assessing the Water Quality of Akwa Ibom State North-West District, Nigeria, Using Water Quality Indices and Palmer Pollution Index. *Ekológia (Bratislava)*, 41, 301-311. <https://doi.org/10.2478/eko-2022-0031>
- Kanhai, G., Agyei-Mensah, S., & Mudu, P. (2021). Population Awareness and Attitudes toward Waste-Related Health Risks in Accra, Ghana. *International Journal of Environmental Health Research*, 31, 670-686. <https://doi.org/10.1080/09603123.2019.1680818>
- Karaoui, I., Arioua, A., Boudhar, A., Hssaisoune, M., Mouatassime, S. E., Ouham-chich, K. A. et al. (2019). Evaluating the Potential of Sentinel-2 Satellite Images for Water Quality Characterization of Artificial Reservoirs: The Bin El Ouidane Reservoir Case Study (Morocco). *Meteorology Hydrology and Water Management*, 7, 31-39. <https://doi.org/10.26491/mhwm/95087>
- Koponen, S., Pulliainen, J., Kallio, K., & Hallikainen, M. (2002). Lake Water Quality Classification with Airborne Hyperspectral Spectrometer and Simulated MERIS Data. *Remote Sensing of Environment*, 79, 51-59. [https://doi.org/10.1016/s0034-4257\(01\)00238-3](https://doi.org/10.1016/s0034-4257(01)00238-3)
- Kuboja, B. N., Mazigo, A. F., Ibengwe, L. J., & Katikiro, R. E. (2024). Legal and Regulatory Framework for Small-Scale Fisheries in Mainland Tanzania: Practical Realities and Opportunities. In J. Nakamura, R. Chuenpagdee, & S. Jentoft (Eds.), *Implementation of the Small-Scale Fisheries Guidelines: A Legal and Policy Scan* (pp. 381-406). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-56716-2_18
- Kundu, R., Aura, C. M., Nyamweya, C., Agembe, S., Sitoki, L., Lung'ayia, H. B. O. et al. (2017). Changes in Pollution Indicators in Lake Victoria, Kenya and Their Implications for Lake and Catchment Management. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use*, 22, 199-214. <https://doi.org/10.1111/lre.12187>
- Li, C., Tao, B., Liu, Y., Zhang, S., Zhang, Z., Song, Q. et al. (2022). Assessment of VIIRS on the Identification of Harmful Algal Bloom Types in the Coasts of the East China Sea. *Remote Sensing*, 14, Article 2089. <https://doi.org/10.3390/rs14092089>

- Li, J. (2016). Assessing Spatial Predictive Models in the Environmental Sciences: Accuracy Measures, Data Variation and Variance Explained. *Environmental Modelling & Software*, *80*, 1-8. <https://doi.org/10.1016/j.envsoft.2016.02.004>
- Liu, S., Lou, S., Kuang, C., Huang, W., Chen, W., Zhang, J. et al. (2011). Water Quality Assessment by Pollution-Index Method in the Coastal Waters of Hebei Province in Western Bohai Sea, China. *Marine Pollution Bulletin*, *62*, 2220-2229. <https://doi.org/10.1016/j.marpolbul.2011.06.021>
- Markogianni, V., Kalivas, D., Petropoulos, G. P., & Dimitriou, E. (2020). Estimating Chlorophyll-A of Inland Water Bodies in Greece Based on Landsat Data. *Remote Sensing*, *12*, Article 2087. <https://doi.org/10.3390/rs12132087>
- Masso, C., Gweyi-Onyango, J., Luoga, H. P., Yemefack, M., & Vanlauwe, B. (2024). A Review on Nitrogen Flows and Obstacles to Sustainable Nitrogen Management within the Lake Victoria Basin, East Africa. *Sustainability*, *16*, Article 4816. <https://doi.org/10.3390/su16114816>
- Mchau, G. J., Makule, E., Machunda, R., Gong, Y. Y., & Kimanya, M. (2019). Harmful Algal Bloom and Associated Health Risks among Users of Lake Victoria Freshwater: Ukerewe Island, Tanzania. *Journal of Water and Health*, *17*, 826-836. <https://doi.org/10.2166/wh.2019.083>
- Mishra, S., & Mishra, D. R. (2012). Normalized Difference Chlorophyll Index: A Novel Model for Remote Estimation of Chlorophyll-A Concentration in Turbid Productive Waters. *Remote Sensing of Environment*, *117*, 394-406. <https://doi.org/10.1016/j.rse.2011.10.016>
- Mitra, S., Tamang, L., & Kumar De, S. (2024). Assessment of the Water Quality of the Mahananda System. In *River Health Assessment: A Study on Mahananda River, India* (pp. 85-108). Springer. https://doi.org/10.1007/978-3-031-76580-3_5
- Nakkazi, M. T., Nkwasa, A., Martinez, A. B., & van Griensven, A. (2024). Linking Land Use and Precipitation Changes to Water Quality Changes in Lake Victoria Using Remote Sensing. <https://doi.org/10.21203/rs.3.rs-3873388/v1>
- Nalumenya, B., Rubinato, M., Catterson, J., Kennedy, M., Bakamwesiga, H., & Wabwire, D. (2024). Assessing the Potential Impacts of Contaminants on the Water Quality of Lake Victoria: Two Case Studies in Uganda. *Sustainability*, *16*, Article 9128. <https://doi.org/10.3390/su16209128>
- Nassali, J., Yongji, Z., & Fangninou, F. F. (2020). A Systematic Review of Threats to the Sustainable Utilization of Transboundary Fresh Water Lakes: A Case Study of Lake Victoria. *International Journal of Scientific and Research Publications (IJSRP)*, *10*, p9890. <https://doi.org/10.29322/ijsrp.10.02.2020.p9890>
- Nativi, S., & Bigagli, L. (2009). Discovery, Mediation, and Access Services for Earth Observation Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *2*, 233-240. <https://doi.org/10.1109/jstars.2009.2028584>
- Nicholson, S. E., Klotter, D., & Hartman, A. T. (2021). Lake-Effect Rains over Lake Victoria and Their Association with Mesoscale Convective Systems. *Journal of Hydrometeorology*, *22*, 1353-1368. <https://doi.org/10.1175/jhm-d-20-0244.1>
- Njagi, D. M., Routh, J., Odhiambo, M., Luo, C., Basapuram, L. G., Olago, D. et al. (2022). A Century of Human-Induced Environmental Changes and the Combined Roles of Nutrients and Land Use in Lake Victoria Catchment on Eutrophication. *Science of The Total Environment*, *835*, Article 155425. <https://doi.org/10.1016/j.scitotenv.2022.155425>
- Nsubuga, F. W. N., Botai, J. O., Olwoch, J. M., Rautenbach, C. J. d., Kalumba, A. M., Tsela, P. et al. (2017). Detecting Changes in Surface Water Area of Lake Kyoga Sub-Basin Using Remotely Sensed Imagery in a Changing Climate. *Theoretical and Applied Climatology*,

- 127, 327-337. <https://doi.org/10.1007/s00704-015-1637-1>
- Nyamweya, C. S., Natugonza, V., Kashindy, B. B., Mangeni-Sande, R., Kagoya, E., Mpomwenda, V. et al. (2023). Response of Fish Stocks in Lake Victoria to Enforcement of the Ban on Illegal Fishing: Are There Lessons for Management? *Journal of Great Lakes Research*, 49, 531-544. <https://doi.org/10.1016/j.jglr.2023.01.001>
- Odada, E. O., Ochola, W. O., & Olago, D. O. (2009). Understanding Future Ecosystem Changes in Lake Victoria Basin Using Participatory Local Scenarios. *African Journal of Ecology*, 47, 147-153. <https://doi.org/10.1111/j.1365-2028.2008.01062.x>
- Outa, N. O., Yongo, E. O., Keyombe, J. L. A., Ogello, E. O., & Namwaya Wanjala, D. (2020). A Review on the Status of Some Major Fish Species in Lake Victoria and Possible Conservation Strategies. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use*, 25, 105-111. <https://doi.org/10.1111/lre.12299>
- Oyedotun, T. D. T., Hamer, E., Nedd, G. A., & Burningham, H. (2025). Advancing Coastal Monitoring: Integrating Spatiotemporal Analyses and Machine Algorithms in G-CAS. *Journal of Coastal Research*, 113, 315-320. <https://doi.org/10.2112/jcr-si113-062.1>
- Rawat, K. S., Sahu, S. R., Singh, S. K., Chander, S., & Gujrati, A. (2023). Water Quality Analysis Using Normalized Difference Chlorophyll Index (NDCI) and Normalized Difference Turbidity Index (NDTI), Using Google Earth Engine Platform. In *2023 International Conference on Modeling, Simulation & Intelligent Computing (MoSiCom)* (pp. 408-413). IEEE. <https://doi.org/10.1109/mosicom59118.2023.10458842>
- Roegner, A., Corman, J., Sitoki, L., Kwena, Z., Ogari, Z., Miruka, J. et al. (2023). Impacts of Algal Blooms and Microcystins in Fish on Small-Scale Fishers in Winam Gulf, Lake Victoria: Implications for Health and Livelihood. *Ecology and Society*, 28, Article 49. <https://doi.org/10.5751/es-13860-280149>
- Sagan, V., Peterson, K. T., Maimaitijiang, M., Sidike, P., Sloan, J., Greeing, B. A. et al. (2020). Monitoring Inland Water Quality Using Remote Sensing: Potential and Limitations of Spectral Indices, Bio-Optical Simulations, Machine Learning, and Cloud Computing. *Earth-Science Reviews*, 205, Article 103187. <https://doi.org/10.1016/j.earscirev.2020.103187>
- Samui, S., Mallik, A., Kumar, D., Rao, S., Dhanya, C. T., & Gosain, A. K. (2025). Identifying the Pollution Sources of River Yamuna through Field Observations and Participatory Approach. *Journal of Earth System Science*, 134, Article No. 41. <https://doi.org/10.1007/s12040-024-02498-7>
- Sent, G., Biguino, B., Favareto, L., Cruz, J., Sá, C., Dogliotti, A. I. et al. (2021). Deriving Water Quality Parameters Using Sentinel-2 Imagery: A Case Study in the Sado Estuary, Portugal. *Remote Sensing*, 13, Article 1043. <https://doi.org/10.3390/rs13051043>
- Simiyu, B. M., Amukhuma, H. S., Sitoki, L., Okello, W., & Kurmayer, R. (2022). Interannual Variability of Water Quality Conditions in the Nyanza Gulf of Lake Victoria, Kenya. *Journal of Great Lakes Research*, 48, 97-109. <https://doi.org/10.1016/j.jglr.2021.10.017>
- Singh, R., Saritha, V., & Pande, C. B. (2024). Monitoring of Wetland Turbidity Using Multi-Temporal Landsat-8 and Landsat-9 Satellite Imagery in the Bisalpur Wetland, Rajasthan, India. *Environmental Research*, 241, Article 117638. <https://doi.org/10.1016/j.envres.2023.117638>
- Sitoki, L., Gichuki, J., Ezekiel, C., Wanda, F., Mkumbo, O. C., & Marshall, B. E. (2010). The Environment of Lake Victoria (East Africa): Current Status and Historical Changes. *International Review of Hydrobiology*, 95, 209-223. <https://doi.org/10.1002/iroh.201011226>
- Smith, S. C., & Rodrigues, D. F. (2015). Carbon-Based Nanomaterials for Removal of Chemical and Biological Contaminants from Water: A Review of Mechanisms and Ap-

- plications. *Carbon*, 91, 122-143. <https://doi.org/10.1016/j.carbon.2015.04.043>
- Sun, L., Chen, Z., Gao, F., Anderson, M., Song, L., Wang, L. et al. (2017). Reconstructing Daily Clear-Sky Land Surface Temperature for Cloudy Regions from MODIS Data. *Computers & Geosciences*, 105, 10-20. <https://doi.org/10.1016/j.cageo.2017.04.007>
- Taabu-Munyaho, A., Kayanda, R. J., Everson, I., Grabowski, T. B., & Marteinsdóttir, G. (2013). Distribution and Exploitation of Nile Perch Lates Niloticus in Relation to Stratification in Lake Victoria, East Africa. *Journal of Great Lakes Research*, 39, 466-475. <https://doi.org/10.1016/j.jglr.2013.06.009>
- Taru, Y. K., & Karwankar, A. (2017). Water Monitoring System Using Arduino with Lab-view. In *2017 International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 416-419). IEEE. <https://doi.org/10.1109/iccmc.2017.8282722>
- Thiemann, S., & Kaufmann, H. (2000). Determination of Chlorophyll Content and Trophic State of Lakes Using Field Spectrometer and IRS-1C Satellite Data in the Mecklenburg Lake District, Germany. *Remote Sensing of Environment*, 73, 227-235. [https://doi.org/10.1016/s0034-4257\(00\)00097-3](https://doi.org/10.1016/s0034-4257(00)00097-3)
- Were, K. O., Dick, Ø. B., & Singh, B. R. (2013). Remotely Sensing the Spatial and Temporal Land Cover Changes in Eastern Mau Forest Reserve and Lake Nakuru Drainage Basin, Kenya. *Applied Geography*, 41, 75-86. <https://doi.org/10.1016/j.apgeog.2013.03.017>
- Youssef, Y. M., Gemail, K. S., Sugita, M., AlBarqawy, M., Teama, M. A., Koch, M. et al. (2021). Natural and Anthropogenic Coastal Environmental Hazards: An Integrated Remote Sensing, GIS, and Geophysical-Based Approach. *Surveys in Geophysics*, 42, 1109-1141. <https://doi.org/10.1007/s10712-021-09660-6>
- Yuan, Z., Li, Q., Ma, X., & Han, M. (2021). Assessment of Heavy Metals Contamination and Water Quality Characterization in the Nanming River, Guizhou Province. *Environmental Geochemistry and Health*, 43, 1273-1286. <https://doi.org/10.1007/s10653-020-00710-3>
- Zhou, H., Li, J., Liao, R., Chen, Y., Liu, T., Wang, Y. et al. (2022). Profile Probing of Suspended Particles in Water by Stokes Vector Polarimetry. *Optics Express*, 30, 14924-14937. <https://doi.org/10.1364/oe.455288>
- Zhu, H., Lin, A., Wang, L., Xia, Y., & Zou, L. (2016). Evaluation of MODIS Gross Primary Production across Multiple Biomes in China Using Eddy Covariance Flux Data. *Remote Sensing*, 8, Article 395. <https://doi.org/10.3390/rs8050395>

Appendix

Ref: Table A1 (annexed).

gID	WPI_2005	WPI_2010	WPI_2013	WPI_2018	WPI_2023
1.0	-34.2399	-30.7259	-62.6316	-77.667	-59.4286
2.0	-46.9078	-22.5217	-63.4532	-39.9888	-35.1199
3.0	-23.252	1.1196	-44.1244	-30.549	40.6863
4.0	-22.7559	-15.4919	-50.2116	-40.6876	17.6657
5.0	-21.7091	-3.8293	-40.7023	-41.2858	41.9226
6.0	-14.1409	-31.9257	-8.6578	-31.888	69.7924
7.0	-22.91	-5.0372	-47.7316	-62.1315	-68.1842
8.0	-30.4425	-2.2611	-53.3179	-83.3205	-68.1894
9.0	-17.316	-10.2719	-99.7855	-47.4283	-75.8059
10.0	-36.9254	-9.9106	-65.0236	-62.6422	-38.1952
11.0	-42.704	-14.091	-71.1888	-68.0235	-63.7381
12.0	-33.1691	-26.2474	-80.2899	-88.4651	-130.171
13.0	-33.9768	-3.7917	-68.6247	-68.7241	-71.3358
14.0	-22.3216	1.6285	-57.9977	-44.5137	-63.5004
15.0	-11.7581	-7.6712	-49.7214	50.7657	-78.0515
16.0	-18.6399	-9.5741	-99.9985	-55.3239	-78.1547
17.0	-24.5488	-8.7728	-66.6176	-24.6436	-61.4202
18.0	-22.378	4.1473	-60.4563	-64.2122	-64.4031
19.0	-30.1742	-14.1078	-72.0845	-70.7343	-67.8555
20.0	-34.69	-14.0639	-54.6356	-70.1969	-85.8479
21.0	-17.1818	-74.5356	-45.7397	-62.5303	-91.6573
22.0	-37.1593	-10.9599	-45.6324	-59.9962	-64.8446
23.0	-37.0463	-19.2341	-59.4508	-68.8175	-71.7097
24.0	-25.8234	-5.4598	-58.3865	-65.3073	-54.7634
25.0	-35.4377	3.2949	-30.527	230.9658	-48.4696
26.0	-44.4978	-18.9322	-65.1571	-63.7735	-64.2563
27.0	-35.1726	-9.574	-63.0624	-76.4997	-57.9494
28.0	-46.0275	-20.9651	-70.6321	-75.9252	-71.2131
29.0	-35.64	-12.6307	-40.0924	-38.2681	-47.6291
30.0	-34.8488	-6.4431	-330.641	-69.98	-90.8133
31.0	-25.3254	-7.8771	-127.062	-75.145	-69.9497
32.0	-41.7544	-19.8618	-84.5524	-74.7565	-61.5407
33.0	-43.6743	-19.1588	-62.8688	-63.2626	-59.7774
34.0	-21.6765	-5.5949	-48.7398	-63.1059	-42.1859
35.0	-39.7252	-14.5781	-259.972	-84.2087	-94.3657