

Research Article

# A Computational Model for Water Quality Analysis and Assessment in Tanzania

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## Abstract

Research on water quality has received much attention in both developing and developed countries. This is because of the fact that, the effects of poor quality of water are detrimental to human beings, animals and the environment. This study is about a computational model for water quality analysis and assessment in Tanzania. Water quality can be understood as the measure of suitability of water based on physical, chemical and biological attributes. Water quality analysis and assessment face several challenges due to population growth, urban land use, agricultural activities, and industrialization. Besides, attempts have been made by the scholars to address the challenges. However, the tools used like titrimetric, electrometric, pH-meter, thermometer and turbidity meter are yet to come up with effective solutions. Because of these, the researcher was compelled to adopt computational model which uses Statistical Analysis System (SAS) software in order to come up with effective solutions concerning water quality analysis and assessment. In this study therefore, the secondary data were collected from Lake Victoria littoral stations under the auspices of the Ministry of Water in Tanzania with the objective to get sufficient information concerning water quality analysis and assessment. Additionally, the collected data were coded in SAS software to analyse independent and dependent variables. SAS software therefore, was employed to obtain central tendency and dispersion as benchmarks in determining quality of water. Also, the Multivariate Linear Regression Model was run to obtain coefficients of estimation, 95% confident limits and p-value. Statistical findings from central tendency and dispersion indicate that, the mean for potential of Hydrogen (pH) was 8.165; for total suspended solids was 3.065 mg/l; chloride displayed a mean of 6.494 mg/l; calcium displayed a mean of 6.421 mg/l; iron had a mean of 0.188 mg/l; magnesium displayed a mean of 3.331 mg/l and sulphate had mean of 2.326 mg/l. Looking closely at all of the above-mentioned water quality parameters, they all align with a Tanzania Bureau of Standards (TBS) and World Health Organization (WHO) as shown on [table 1](#). Findings from the Multivariate linear regression model shows that: First, iron had a p-value of 0.0153, magnesium 0.0347 and total hardness had a p-value of 0.001. All of these were statistically significant in the analysis and assessment of water quality as shown on [table 2](#). The study concludes that, the water quality in Lake Victoria complies with both TBS and WHO standards as explained above.

## Keywords

Littoral, Computational Model, Water Quality Parameters, Lake Victoria

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## 1. Introduction

Water quality has been an area of interest among scholars worldwide and Tanzania in particular because of its detrimental effects on human beings, animals and the environments. In attempt to define the quality of water, many scholars around the globe consider such parameters as the chemical, physical, and biological characteristics of water [11-13, 7]. According to these scholars, quality of water is a measure of the suitability of water for a particular purpose such as drinking or swimming. They further argue that the contents of water quality parameters are determined by its characteristics like chloride ( $\text{Cl}^-$ ), calcium ( $\text{Ca}^{2+}$ ), dissolved oxygen (DO), electrical conductivity (EC), iron ( $\text{Fe}^{2+}$ ), magnesium ( $\text{Mg}^{2+}$ ), potential of hydrogen (pH), sulphate ( $\text{SO}_4^{2-}$ ), total alkalinity (TA), total dissolved solids (TDS), total hardness (TH), total suspended solids (TSS), temperature (T) and turbidity (Turb).

The analysis and assessment of water quality currently has been done using readymade tools such as titrimetric, flame photometer, electrometric, pH-meter, gravimetric, Flame Atomic Absorption Spectroscopy (FAAS), thermometer, spectrophotometric and turbidity meter which may be defective [7]. However, these tools have shown some significant impact on water quality analysis and assessment in both Tanzania and developed countries [1, 9]. Despite this effort to determine the quality of water in Tanzania and sub-Saharan Africa for example, where access to clean water supplies is limited, still the prevalence of waterborne diseases such as cholera, typhoid, dysentery and bilharzia is high. Each day, more than 2,200 children die of diseases caused by poor water quality [18, 16].

Additionally, studies which were conducted in Pakistan found that only 20% of the population in the country has access to safe drinking water, while the remaining 80% is forced to use unsafe water due to scarcity [2, 5, 15].

Notwithstanding the efforts put forward by the above scholars to analyse and assess the quality of water as well as showing the associated consequences, the tools used do not provide comprehensive and effective solutions towards addressing the issue of quality water and hence these scholars leave much to be desired. Based on this fact therefore, the researcher was compelled to adopt a computational model to address some of the flaws encountered in analysing and assessing water quality. The computational model adopted aims to overcome challenges in water quality analysis and assessment by employing advanced algorithms to enhance prediction accuracy, efficiency, and cost-effectiveness.

The justification to use the computational model in this study is based on the fact that, this kind of analysis and assessment is lacking. Also, the model enables a researcher to investigate the relationships between independent variables

(denoted as  $x$ ) and dependent variables (denoted as  $y$ ). This model also allows researchers to examine how multiple independent variables (water quality parameters) affect dependent variables (water quality) simultaneously. Additionally, the computational model can be used for prediction purposes because of its accuracy which is attributed by several factors such as its ability to consider multiple predictors, its simplicity and interpretability, and the availability of statistical techniques for testing and optimization [4, 6].

## 2. Materials and Methods

This section presents the materials and methods used in the paper. It covers the area of study, research design, data collection methods/tools, analysis and conceptual framework.

### 2.1. The Area of Study

This study was conducted around Lake Victoria basin in Tanzania. Being the largest tropical basin lake in Africa, it was therefore thought of by the researcher that it would offer candid information concerning Tanzania littoral water [11]. In the three East African countries, Lake Victoria serves both Tanzania pelagic (TP) and Littoral (TL), Kenya pelagic (KP) and littoral (KL), and Uganda pelagic (UP) and littoral stations (UL) for monitoring water quality.

### 2.2. Research Design

This study involved a step-by-step study design from the initial process of data collection, data cleaning, data analysis and writing of the final work. This experimental based, cross-sectional study design involving quantitative method using Statistical Analysis System (SAS) software which incorporates a computational model was adopted in this study. This model addresses most of the flaws encountered by earlier researchers in analysing and assessing the quality of water in Tanzania. It also acts as blueprint towards a comprehensive understanding of the adverse impacts of poor water quality on human health, animals and the environment.

### 2.3. Data Collection

This study involves the use of various secondary data collection tools including titrimetric, flame photometer, electrometric, pH-meter, gravimetric, Flame Atomic Absorption Spectroscopy (FAAS), thermometer, spectrophotometric and turbidity meter.



## 2.4. Data Analysis

Unlike the previous studies which involved the use of readymade tools in the analysis and assessment of water quality, data in this study involved the use of Statistical Analysis System (SAS) software in which descriptive statistics measure of central tendency and dispersion were obtained in which the outcomes were mean and standard deviation. Also, the Multivariate linear regression model which employs SAS software was run to obtain coefficients of estimation, 95% confident limits and p-value.

### 2.4.1. Descriptive Statistics Measure of Central Tendency and Dispersion

Descriptive statistics were used to measure central tendency and dispersion. The objective was to determine the physical and chemical characteristic of water in Lake Victoria. Water quality was assessed as per Tanzania Bureau of Standards and World Health Organization standards. The descriptive statistics measure of central tendency and dispersion are presented by the formula below.

$$\text{Mean}(\bar{x}) = \frac{\sum fx}{n} \quad (1)$$

$$\text{Standard Deviation (STD)} = \sqrt{\frac{\sum f(x-\bar{x})^2}{n}} \quad (2)$$

Where,

x= water quality parameters

n= number of parameters

f= frequency

Based on the formula above, the input data were coded and output were managed by using the Statistical Analysis System (SAS) programming language in order to ensure accurate results of central tendency and dispersion.

### 2.4.2. The Multivariate Linear Regression Model

The Multivariate Linear Regression Model was adopted in

order to obtain estimation of coefficients, 95% confident limits and p-value. The computational model was used as a tool for adaptive management and enabling continuous assessment of water quality management strategies over time, and to conduct scenario analysis on the potential impacts of different factors on water quality. The independent variables which were considered in data analysis include chloride ( $\text{Cl}^-$ ), calcium ( $\text{Ca}^{2+}$ ), dissolve oxygen (DO), electrical conductivity (EC), iron ( $\text{Fe}^{2+}$ ), magnesium ( $\text{Mg}^{2+}$ ), potential of hydrogen (pH), sulphate ( $\text{SO}_4^{2-}$ ), total alkalinity (TA), total dissolved solids (TDS), total hardness (TH), total suspended solids (TSS), temperature (Temp) and turbidity (Turb). Water quality therefore was used as the dependent variable and water quality parameters were used as independent variable.

The independent and dependent variables are presented in the equation below.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \dots + \beta_n x_n + \epsilon \quad (3)$$

Where,

y = Dependent variable

$x_1, x_2, x_3 \dots x_n$  = Independent variable

$\beta_0$  = Constant

$\beta_1, \beta_2, \beta_3 \dots \beta_n$  = Coefficients of the independent variables

$\epsilon$  = is the random error of the dependent variables.

The multivariate linear regression equation was coded and input and output data were managed. Also, algorithms were defined within a Multivariate linear regression model.

## 2.5. Conceptual Framework

The conceptual framework was designed in order to illustrate the expected relationship between independent and dependent variables in both central tendency and dispersion, and multivariate linear regression model.

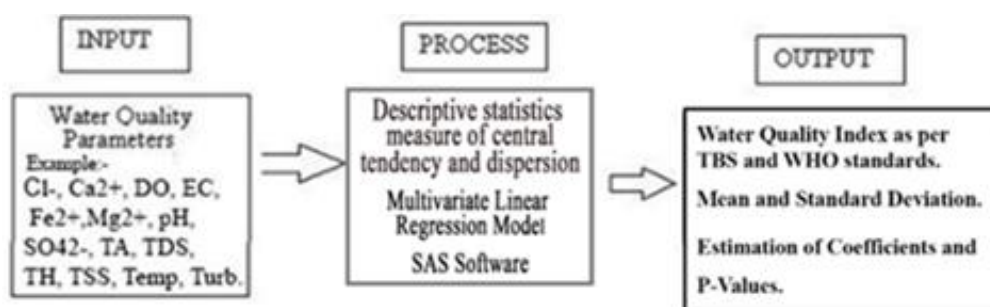


Figure 3. Input - Process - Output (IPO) conceptual framework

### 3. Results

Descriptive statistics measure of central tendency and dispersion using Statistical Analysis System software (SAS) was employed in the analysis of data in order to obtain mean and standard deviation. Also, this software which incorporates the Multivariate linear regression model was run to obtain coefficients of estimation, 95% confident limits and p-value. The objectives were: to determine the physical and chemical characteristics of water in Lake Victoria littoral. Additionally, the Multivariate linear regression model was adopted as a tool

which enables continuous assessment of water quality and management strategies over time. Furthermore, the model was used to conduct scenario analysis on the potential impact of different factors on water quality.

#### 3.1. Descriptive Statistical Measures of Central Tendency and Dispersion

The descriptive statistical measures of central tendency and dispersion in Tanzania Littoral are presented in Table 1.

**Table 1.** Central Tendency and Dispersion for Tanzania Littoral (TL).

Parameters	Mean	Min	Max	STD	WHO/TBS Standards
Cl <sup>-</sup>	6.494	1.98	17.4	3.0369	250
Ca <sup>2+</sup>	6.421	0.48	18	2.6582	75
D O	3.842	1	6	1.2698	4.9
EC	111.2	59	355.88	30.9979	-
Iron	0.188	0	0.39	0.1105	0.3
Mg <sup>2+</sup>	3.331	0	10.46	1.5797	30
pH	8.165	6.15	9.7567	0.8131	6.5-8.5
SO <sub>4</sub> <sup>2-</sup>	2.326	0.42	9.87	1.7626	250
T A	59.62	0	310	29.0238	200
TDS	61.32	0.1	177.94	21.9216	500
TH	34.98	3.9	310	22.0859	300
TSS	3.065	1	9	2.0638	60
Temp	24.81	22.2	29.6817	1.1077	-
Turb	4.165	1	9.26	2.5311	25

Table 1 shows that chloride had a mean of 6.494 mg/l and a standard deviation of 3.0369 mg/l, which is relatively high. The mean value for calcium was 6.421 mg/l with a standard deviation of 2.6582 mg/l. Among the data collected, dissolved oxygen found to have a mean of 3.842 mg/l and a standard deviation of 1.2698 mg/l. Electrical conductivity found to have a mean of 111.2  $\mu$ S/cm and a standard deviation of 30.9979  $\mu$ S/cm, of which it exhibited low dispersion. A mean for iron was 0.188 mg/l and a standard deviation was 0.1105 mg/l also demonstrated high variability. Similarly, the mean for magnesium was 3.331 mg/l and a standard deviation of 1.5797 mg/l. This also shows high variability. The pH value had a mean of 8.165 and a standard deviation of 0.8131, which is moderately dispersed.

Additionally, the mean for sulphate was 2.326 mg/l and a standard deviation of 1.7626 mg/l, which also exhibits high variability. Total alkalinity had a mean of 59.62 mg/l and a

standard deviation of 29.0238 mg/l. This shows significant variability. Total dissolved solids scored a mean of 61.32 mg/l and a standard deviation of 21.9216 mg/l showing a relatively low dispersion. The mean for total hardness was 34.98 mg/l and a standard deviation was 22.0859 mg/l which demonstrates high variability. Total suspended solids had a mean of 3.065 mg/l and a standard deviation of 2.0638 mg/l which also exhibit high variability. Temperature got a mean of 24.81 °C and a standard deviation of 1.1077 °C. This demonstrates a moderate dispersion as well. The mean for turbidity which demonstrates high variability was 4.165NTU and a standard deviation was 2.5311NTU. This demonstrates high variability too.

Based on the descriptive statistical measures for central tendency and dispersion given above, it should be noted that high chloride level can affect the taste of water and may corrode metal pipes and equipment. High calcium can also con-

tribute to water hardness. Excessive dissolved oxygen can lead to supersaturation in water. High electroconductivity often means high concentrations of dissolved salts, corrosive of pipes and potential contamination from metals leaching into the water supply. High magnesium level contributes to water hardness. Excess iron can cause discoloration and staining of water fixtures and laundry. It can also affect water taste and odour. High or low pH levels can affect water quality because of acidic and alkalinity intricacies. Evaluated sulphate levels can have a laxative effect on the taste of water. They can also contribute to the formation of sulphide compounds, which can be harmful. High total alkalinity can buffer against pH changes but can also lead to scaling and contribute

to water hardness. High total hardness level causes hard water scaling in pipes and appliances and leads to mineral deposits. Excess total suspended solids can cloud water and reduce light penetration. High total dissolved solids levels can lead to a salty or brackish taste in water.

### 3.2. Multivariate Linear Regression Model

The objectives of this paper were to use the computational model to assess the quality of water over time and, to conduct scenario analysis on the potential impacts of different factors on water quality. The findings of this study are shown in [Table 2](#).

**Table 2.** Multivariate linear regression analysis.

Analysis of Maximum Likelihood Parameter Estimates				
Parameters	Estimation of coefficients	Wald 95% Confidence limits		P- Value
		low	High	
Intercept	2.8098	1.6673	4.7351	0.0001
Cl <sup>-</sup>	0.9957	0.9893	1.0022	0.1964
Ca <sup>2+</sup>	0.9995	0.9920	1.0070	0.9006
DO	0.9919	0.9773	1.0067	0.284
EC	0.9999	0.9993	1.0006	0.7901
Iron	0.8099	0.6831	0.9603	0.0153
Mg <sup>2+</sup>	1.0129	1.0009	1.0249	0.0347
pH	0.9803	0.9561	1.0050	0.1173
SO <sub>4</sub> <sup>2-</sup>	1.0047	0.9930	1.0165	0.429
TA	1.0002	0.9993	1.0011	0.6431
TDS	1	0.9992	1.0009	0.9163
TH	0.9964	0.9954	0.9975	0.0001
TSS	0.9943	0.9851	1.0036	0.2259
Temp	1.0113	0.9931	1.0297	0.2265
Turb	1.0041	0.9961	1.0122	0.3112
Scale	1.1147	1.1013	1.1299	

Based on the data presented in [table 2](#) Chloride showed a negligible effect on water quality, with an estimation of coefficients of 0.9957, 95% CI (0.989 - 1.002) and a non-significant p-value of 0.1989. Magnesium demonstrated a significant positive impact on water quality, with an estimation of coefficients of 1.0129, 95% CI (1.001 - 1.025) and a statistically significant p-value of 0.0347. Calcium had an estimation of coefficients of 0.9995, 95% CI (0.992 - 1.007)

and a non-significant p-value of 0.9006, indicating no significant effect on water quality.

Discharged oxygen exhibited a marginal effect on water quality, with an estimation of coefficients of 0.9919, 95% CI (0.9773 - 1.0067) and a non-significant p-value of 0.284. Similarly, electrical conductivity had a minimal effect, with an estimation of coefficients of 0.9999, 95% CI (0.9993 - 1.0006) and a non-significant p-value of 0.7901.

Iron accounted for a significant reduced effect on water quality, with an estimation of coefficients of 0.8099, 95% CI (0.6831 - 0.9603) and a statistically significant p-value of 0.0153. Additionally, magnesium demonstrated a significant increased impact, as mentioned earlier, with an estimation of coefficients of 1.0129, 95% CI (1.0009-1.0249) and a statistically significant p-value of 0.0347. Potential of Hydrogen (pH) depicted a negligible effect, with an estimation of coefficients of 0.9803, 95% CI (0.9560 - 1.0050) and a non-significant p-value of 0.1173.

The estimation of coefficients for sulphate was 1.0047, 95% CI (0.9930 - 1.01653) with a p-value of 0.429, indicating that the result is not statistically significant. Similarly, total alkalinity had an estimated coefficient of 1.0002, 95% CI (0.9930 - 1.0011) with a p-value of 0.6431, also showing no statistical significance. Total dissolved solids portrayed an estimation of coefficients of 1, 95% CI (0.9992 - 1.0009) with a p-value of 0.9163, indicating no statistical significance.

On the other hand, total hardness exhibited an estimation of coefficients of 0.9964, 95% CI (0.9954 - 0.9975) with a statistically significant p-value of 0.0001. Total suspended solids displayed an estimation of coefficients of 0.9943, 95% CI (0.9851 - 1.0036) with a p-value of 0.2259, which is not statistically significant.

Temperature got an estimation of coefficients of 1.0113, 95% CI (0.9931 - 1.0297) with a p-value of 0.2265, indicating no statistical significance. Similarly, turbidity got an estimation of coefficients of 1.0041, 95% CI (0.9961 - 1.0121) with a p-value of 0.3112, also showing no statistical significance. Based on the data presented in [table 2](#), the results indicate that the model effectively explain the high percentage of variance across all parameters utilized in the test. The analysis suggests that the quality of water in Lake Victoria can be significantly influenced by alterations in the concentrations of certain constituents, specifically iron, magnesium, and total hardness ( $p < 0.05$ ).

## 4. Discussion

This section discusses the findings obtained from the study. The study focused on assessment of water quality in Tanzanian Lake Victoria littoral (TL). This discussion takes into account of the data obtained from the Ministry of water. Specifically, the discussion focuses on the results of descriptive statistical measure of central tendency and dispersion, and the Multivariate linear regression model. In the course of discussion, this paper makes a retrospection of the findings obtained from related studies as well as taking into consideration the objectives of the current study.

### 4.1. Central Tendency and Dispersion

The findings discussed here are those which are presented in section 3.2 and they show that, the central tendency and dispersion for analysis and assessment of water quality in

Tanzanian Lake Victoria Littoral align with WHO and TBS standards altogether (see [table 1](#)). Besides, these findings concur with those of scholars who inevitably conducted similar studies in various countries including Ethiopia, Democratic Republic of Congo and the Philippines [5, 10, 14, 17]. For example, a study which was conducted in Lake Tana came up with the following findings: The alkalinity mean value was 123.78 mg/l. On the other hand, the total alkalinity mean value for Lake Victoria in Tanzania was 59.62 mg/l which is lower than that of Lake Tana. This difference is attributed by the fact that, Lake Tana receives more input from geological composition of the surrounding land which influences the mineral content of lake water.

In this study, the data from Lake Victoria show that, the total hardness mean value was 34.98 mg/l. When compared with the study of Wondim (ibid) it shows that Lake Tana in Ethiopia, had the mean value of 114.29 mg/l. Therefore, the total hardness value of Lake Tana was found to be higher than that of Lake Victoria because of weathering processes. The rate and extent of weathering of rocks and minerals in the catchment area influence the number of dissolved ions in lake water.

The pH mean value of Lake Victoria was 8.165 in which when compared with pH mean value of Lake Tana, findings indicate that, the pH mean value of Lake Tana was 8.1 which was lower than that of Lake Victoria implying that the waters of Lake Tana are seemingly better than those of Lake Victoria. This is because of the differences caused by natural variability and buffering capacity.

The temperature values of Lake Tana ranged between 17 to 31 °C with the overall mean value of 23.22 °C. When compared with the temperature values of Lake Victoria in Tanzania, the mean values varied between 22.2 to 29.68 °C with the overall mean value of 24.81 °C. The temperature value of Lake Victoria was found to be higher than that Lake Tana. This suggests that the temperature of Lake Victoria and Lake Tana seems to be more or less the same because of their geographical locations whereas, Lake Victoria, being located closer to the equator experiences less tropical climate as opposed to Lake Tana.

The electroconductivity mean value of Lake Tana was 124.5 µs/cm while the electroconductivity mean value of Lake Victoria was 111.2 µs/cm. Therefore, this difference suggests that Lake Tana has higher electroconductivity compared to that of Lake Victoria because of regional climate and hydrology.

The total dissolved solids mean value of Lake Tana was 68.33 mg/l while the total dissolved solids mean value of Lake Victoria was 61.32 mg/l. Therefore, total dissolved solids value of Lake Tana was found to be higher than that of Lake Victoria because of inflow, outflow, and lake depth.

The turbidity mean value of Lake Tana was 63.67NTU. When compared with turbidity mean value of Lake Victoria which is 4.165NTU, the former mean turbidity value was higher than the latter. This is because of climate and rainfall

patterns [17].

In addition, another study on central tendency and dispersion was conducted and came up with the following findings:

Chloride had a mean of 131.22 mg/l and standard deviation of 104.33 mg/l. These findings differ from those obtained in current study whereas the mean for water quality in Lake Victoria is 6.494 mg/l and standard deviation is 3.0369 mg/l with a low range compared to that of Laguna de Baý. The reason for variation is ecological difference in that, the ecological health and biodiversity of each lake can also affect chloride concentrations. Different species of aquatic organisms and vegetation interact differently with chloride ions, potentially influencing their concentration in the water column.

On the side of pH, Lake Laguna showed the pH of 8.04 and the STD of 0.73 in which when these findings are compared to those of Lake Victoria, they show variations in that, the mean for Lake Victoria is 8.165 and STD is 0.8131. These differences are caused by the sources of water and flow. The sources of water feeding into the lakes and the flow patterns can also influence pH levels. Lakes receiving water from rivers, streams, or runoff with different chemical compositions will show variations in pH. Additionally, the rate of water turnover and mixing within the lakes can affect the consistency of pH readings.

Another aspect which these scholars looked at, was temperature whereby the mean for water quality analysis in Lake Laguna was 27.75 °C and the STD was 2.41 °C. These findings differ from those of Lake Victoria in which the mean was 24.81 °C and the STD was 1.1077 °C. This difference is caused by altitude and solar radiation. Altitude influences temperatures in that, those areas with higher altitude lakes tend to have cooler temperatures due to the lower atmospheric pressure and cooler ambient temperatures. Lake Laguna is at a lower altitude compared to Lake Victoria and therefore, the amount of solar radiation a lake receives can affect its temperature. Factors such as cloud cover, shading from surrounding vegetation, and the angle of sunlight can influence the extent of solar heating. Lake Laguna may receive more direct sunlight or have less cloud cover compared to Lake Victoria [5].

Another parameter that was considered was total dissolved solids in which findings showed a mean of 35.64 mg/l and STD of 15.89 mg/l. These differ from Lake Victoria data in which the current study shows a mean of 3.065 mg/l and the STD of 2.0638 mg/l. The difference is caused by pollution levels from various sources, including industrial waste, sewage discharge, and stormwater runoff. Lake Laguna has higher levels of pollution compared to Lake Victoria.

Similarly, the turbidity of Laguna de Baý showed a mean of 51.13 mg/l and the STD of 17.06 mg/l which greatly differ from that of Lake Victoria with a mean of 4.165 mg/l and the STD of 2.5311 mg/l. This is caused by sediment and erosion in which higher levels of soil erosion in the watershed of Laguna de Baý can lead to increased sediment entering the lake and raising turbidity [5].

There was another scholar who was interested in central tendency and dispersion [10]. These scholars conducted a similar study particularly in the Democratic Republic of Congo and in Lake Kivu in particular. The results of their study show the following in DRC Littoral stations:

Discharged oxygen showed a mean of 5.95 mg/l and standard deviation of 0.6375 mg/l. These findings do not differ much from those obtained in the current study, whereas the mean for water quality in Lake Victoria is 3.842 mg/l and standard deviation is 1.2698 mg/l. This difference therefore is due to physical characteristics of the lakes in which the depth, water flow, and mixing patterns of the lakes differ hence affecting how oxygen is distributed within the water column. For example, Lake Kivu's unique stratification and volcanic activity might influence higher oxygen levels in certain areas.

Similarly, the electroconductivity of Lake Kivu showed a mean of 1192.7875 µs/cm and the STD of 26.2125 µs/cm which greatly differ from that of Lake Victoria whereas the mean of electroconductivity in Lake Victoria is 111.2 µs/cm and the STD was 30.9979 µs/cm. These findings show the significant differences in electroconductivity (EC) between Lake Kivu and Lake Victoria, and the reasons for these are geological differences whereby Lake Kivu is situated in a volcanic region with significant geothermal activity, leading to higher mineral content in the water. The dissolution of minerals such as salts, carbonates, and other ions from volcanic rocks contributes to the higher EC compared to Lake Victoria.

Looking at pH, Lake Kivu had a mean of 8.8875 and standard deviation of 0.325. These findings differ from those obtained from the current study in which the mean for water quality in Lake Victoria is 8.165 and standard deviation is 0.8131. By observing the data from the two Lakes they show the slight difference, which is attributed by volcanic activity and geochemical influences in which Lake Kivu is influenced by volcanic activity, leading to the presence of alkaline minerals such as carbonates and bicarbonates, which can raise the pH level. The volcanic geology contributes to a more basic environmental volcanic activity compared to Lake Victoria.

In the same way, the total dissolved solids of Lake Kivu indicated a mean of 0.658765 mg/l and the STD of 0.0125 mg/l which greatly differ from that of Lake Victoria in that, a mean of Lake Victoria is 61.32 mg/l and the STD is 21.9216 mg/l. From these findings the differences can be attested by differences in water inflows and sources in that Lake Kivu receives a substantial amount of water from underground springs, which often have fewer dissolved solids compared to surface runoff. In contrast, Lake Victoria's TDS is heavily influenced by surface runoff that carries sediments, nutrients, and pollutants from surrounding agricultural and urban areas, hence increasing the TDS significantly.

To postulate on temperature, results from Lake Kivu depicted a mean of 24.3875 °C and standard deviation of 0.4125 °C. Taking into considerations of the findings from Lake Victoria they show a mean of 24.81 °C and the STD of

1.1077 °C altogether. Therefore, we can deduce that Lake Victoria had a low mean compared to Lake Kivu. These differences however are caused by geographical location and climate in which Lake Kivu is situated at a higher altitude compared to Lake Victoria, which can result in slightly cooler and more stable temperatures. The difference in altitude affects the overall climate, with Lake Victoria experiencing slightly warmer temperatures due to its lower elevation.

In the same context, this study looked at the turbidity of Lake Kivu which showed a mean of 8.0875 mg/l and the STD of 4.275 mg/l which greatly differ from that of Lake Victoria with a mean of 4.165 mg/l and the STD of 2.5311 mg/l. The differences in turbidity between Lake Kivu and Lake Victoria can be attributed to sediment resuspension and erosion whereby Lake Kivu's steep shorelines and underwater geothermal activity can cause frequent sediment resuspension, increasing turbidity. In contrast, Lake Victoria has flatter shorelines and less frequent disturbance of sediments, leading to lower turbidity.

Some other scholars who ventured into the area of central tendency and dispersion were those who conducted a similar study in the Philippines particularly in Lake Mainit [14]. The study involved some littoral stations and came up with the following findings:

On the issue of discharged oxygen, findings from Lake Mainit indicated a mean of 7.69 mg/l and standard deviation of 1.69 mg/l. These findings differ from those obtained from Lake Victoria in which the mean for water quality is 3.842 mg/l and standard deviation is 1.2698 mg/l. When these findings were compared with Lake Victoria data, they showed a difference which is caused by trophic state of the lakes whereas Lake Mainit and Lake Victoria are in different trophic states. Lake Mainit might be in a more oligotrophic (low nutrient, high oxygen) state compared to Lake Victoria, which is in a more eutrophic (high nutrient, lower oxygen). Eutrophic lakes often have lower dissolved oxygen levels due to higher levels of organic matter and subsequent decomposition.

In the same vein, the electroconductivity of Lake Mainit showed a mean of 172.03  $\mu\text{S}/\text{cm}$  and the STD of 13.56  $\mu\text{S}/\text{cm}$  which greatly differ from that of Lake Victoria with a mean of 111.2  $\mu\text{S}/\text{cm}$  and the STD of 30.9979  $\mu\text{S}/\text{cm}$ . This is because of geological composition and mineral content whereby the electroconductivity of Lake Mainit is influenced by the surrounding geology, which includes mineral-rich rocks and sediments that leach ions into the water, increasing its conductivity. In contrast, Lake Victoria's geological composition may contribute fewer dissolved ions, resulting in lower EC values.

On the side of pH, Lake Mainit showed a mean score of 8.12 and standard deviation of 0.50. These findings differ from those obtained from Lake Victoria in that, the mean for water quality analysis and assessment in Lake Victoria is 8.165 and the standard deviation is 0.8131. These slight differences are due to buffering capacity and water chemistry

whereby Lake Mainit may have a higher buffering capacity due to the presence of dissolved minerals that stabilize the pH, reducing fluctuations. Lake Victoria's pH might vary more due to factors like organic matter decomposition, nutrient inputs, or episodic pollution events that can cause temporary pH shifts.

In connection to the above, total dissolved solids had a mean of 83.37 mg/l and standard deviation of 5.88 mg/l. These findings differ from those obtained from the current study whereas the mean for water quality in Lake Victoria is 61.32 mg/l and standard deviation is 21.9216 mg/l with a difference of 22.05 mg/l compared to that of Lake Mainit. The reasons for differences are lower variability due to stable input sources in that the low standard deviation in Lake Mainit suggests that the TDS sources are relatively stable. These differences are consistent groundwater inflows or springs with steady mineral content. Lake Victoria's higher variability in TDS indicates fluctuating inputs from pollution, runoff, and rainfall, which can vary widely in dissolved solids.

Looking closely at temperature, Lake Mainit had a mean of 29.92 °C and standard deviation of 1.34 °C. The findings from Lake Mainit differ from those obtained from Lake Victoria whereas the current study show the mean of 24.81 °C and subsequent STD of 1.107 °C. These differences however are noticeable because of evaporation and heat retention and that Lake Mainit may have higher evaporation rates due to its warmer environment, which could lead to greater heat retention in the water. Lake Victoria, with its relatively lower temperatures, may lose heat more efficiently, maintaining cooler water temperatures.

Similarly, the turbidity of Lake Mainit showed a mean of 1.37 mg/l and the STD of 0.46 mg/l which greatly differ from that of Lake Victoria with a mean of 4.165 mg/l and the STD of 2.5311 mg/l. This could be accounted by water mixing and stratification in which Lake Mainit's smaller size or different mixing patterns might lead to less resuspension of sediments compared to Lake Victoria. Lake Victoria's larger surface area and wind-driven mixing can cause more frequent resuspension of bottom sediments, increasing turbidity [14].

## 4.2. Multivariate Linear Regression Model

In the analysis and assessment of water quality in Lake Victoria littoral, the Multivariate Linear Regression Model was run in order to obtain estimation of coefficients, 95% confident limit and p-value. This went hand in hand with the discussion of specific objectives of the study which include creation of an enabling continuous assessment of water quality management strategies over time and conducting scenario analysis on the potential impacts of different factors on water quality. The findings from this study are shown on [table 2](#) above.

The above findings (see [table 2](#)) can be compared with similar studies which were conducted in the same field [3, 8, 10, 14].

In terms of Multivariate linear regression model which was run in order to determine the p-value of water quality parameters, the following were the findings:

In terms of the discharged oxygen a study was conducted in Lake Kivu and the findings came up with a p-value of 0.007, which was statistically significant. This was compared to Lake Victoria data where the p-value for discharged oxygen was 0.284 demonstrating no statistical significance. The reasons for this difference are caused by differences in environmental conditions in which Lake Kivu and Lake Victoria have distinct environmental conditions that can affect the levels of discharged oxygen. For instance, Lake Kivu's volcanic activity and stratification might lead to significant variations in dissolved oxygen, making the observed differences more statistically significant. In contrast, Lake Victoria's discharged oxygen might be influenced by a range of factors with more variability, leading to less clear-cut differences [10].

Another aspect to be given attention by the above scholars was pH whereas Lake Kivu had a p-value of 0.037, which was statistically significant. This was compared to Lake Victoria data where the p-value for pH was 0.1173 demonstrating no statistical significance. The difference in statistical significance for pH between Lake Kivu and Lake Victoria can be attributed by temporal and spatial variability whereby pH levels can vary over time and space within a lake. If Lake Kivu has more stable or less variable pH levels due to its unique environmental conditions, which might show more significant differences. Lake Victoria might experience more fluctuations or a broader range of pH values, which can affect the significance of the findings.

Looking at the electroconductivity, Lake Kivu had a p-value of 0.012, which was statistically significant. This was compared to Lake Victoria data whereby the p-value for electroconductivity was 0.7901 demonstrating no statistical significance. The difference in statistical significance for electroconductivity between Lake Kivu and Lake Victoria are caused by differences in dissolved solids whereby Lake Kivu's high electroconductivity is likely due to higher levels of dissolved solids and minerals in the water. If the factors influencing electroconductivity are more stable or pronounced in Lake Kivu, this can lead to significant results. Lake Victoria might have more variable or lower levels of dissolved solids, which could reduce the ability to detect significant differences.

In terms of total dissolved solids, Lake Kivu had a p-value of 0.169, which was not statistically significant. This was contrasted to Lake Victoria data where the p-value for total dissolved solids was 0.9163 demonstrating no statistical significance. These similarities are due to homogeneity in catchment characteristics. If the catchment characteristics and land use around both lakes are similar, they might contribute similar amounts of dissolved solids to the lakes, resulting in non-significant differences.

The Temperature in Lake Kivu had a p-value of 0.000,

which was statistically significant. This was compared to Lake Victoria data where the p-value for temperature was 0.2265 demonstrating no statistical significance. The reasons for this difference are due to the geographic location and climatic conditions surrounding each lake. Lake Kivu's unique climatic conditions might result in more pronounced temperature changes compared to Lake Victoria.

The Turbidity in Lake Kivu had a p-value of 0.000, which was statistically significant. This was compared to Lake Victoria data where the p-value for turbidity is 0.3112 demonstrating no statistical significance. The reasons for this difference are due to sources of turbidity in which Lake Kivu might experience different sources of turbidity compared to Lake Victoria. For example, Lake Kivu could have more frequent or intense inflows of sediments or pollutants that affect turbidity levels [10].

A study was conducted on Lake Mainit littoral in the Philippines and came up with the following findings:

For the case of discharged oxygen, Lake Mainit indicated a p-value of 0.02, which was statistically significant. These data were compared to those from Lake Victoria in which the p-value for discharged oxygen was 0.284 demonstrating no statistical significance. The reasons for these differences are due to ecological factors in which the biological activity in each lake, such as the presence of aquatic plants, algae, and microbial communities, can influence dissolved oxygen levels. Lake Mainit might have a different ecological balance that affects oxygen levels more significantly [14].

Scholars who conducted a similar study considered electroconductivity as a parameter for water quality analysis and assessment, and the findings indicate that, Lake Mainit had a p-value of 0.015, which was statistically significant. On the other hand, these results were compared to Lake Victoria data in which the p-value for electroconductivity was 0.7901 demonstrating no statistical significance. This contrast on the findings can be accrued by electrolytes whereby electroconductivity is influenced by the concentration of dissolved ions in the water. Lake Mainit might have different sources of electrolytes or higher concentrations of ions due to geological or hydrological factors, leading to more significant variations in electroconductivity [14].

Besides, the above scholars had to look onto the pH level of water quality in Lake Mainit and the findings show that this Lake had a p-value of 0.001, which was statistically significant. These findings are contrary to Lake Victoria data where the p-value for pH was 0.1173 demonstrating no statistical significance. To explain this difference, we have to make a retrospection to account for this difference in which results show that the latter is caused by water chemistry whereby the chemical composition of the water in each lake can affect pH. Lake Mainit might have higher concentrations of substances that affect pH, such as acidic or alkaline compounds, compared to Lake Victoria.

Additionally, the total dissolved solids in Lake Mainit had a p-value of 0.173, which was not statistically significant. This

was compared to Lake Victoria data where the p-value for total dissolved solids was 0.9163 demonstrating no statistical significance. The reason for this difference is due to consistency of TDS levels whereby both lakes might have relatively stable or consistent levels of total dissolved solids, resulting in p-values that do not reach statistical significance. If the levels of TDS do not vary significantly or if there is little difference between the data points, it can lead to non-significant results.

Moreover, the findings from Lake Mainit indicated a p-value of 0.001 for temperature which was statistically significant. In comparison with the findings from Lake Victoria, the results show a p-value of 0.2265 for temperature demonstrating no statistical significance. The reason for this difference is seasonal and environmental changes in which Lake Mainit might experience more significant seasonal temperature fluctuations or environmental changes compared to Lake Victoria. These fluctuations can contribute to significant differences in temperature data [14].

Lastly, the above research focused on turbidity in water quality analysis and assessment in Lake Mainit and they came up with a p-value of 0.0091, which was statistically significant. To compare these findings with those from Lake Victoria, we can establish that the p-value for turbidity was 0.3112 demonstrating no statistical significance. This difference can be accounted by fact that the physical characteristics of Lake Mainit, such as its catchment area, geology, and hydrological processes, could contribute to more significant turbidity variations. For example, volcanic activity or mining in the area surrounding Lake Mainit might contribute to higher turbidity levels [14].

Additionally, a study was conducted in Urban Lake, located in the Noyyal River Basin, the textile capital of India [3]. Their data were compared with those of Lake Victoria and explained in the subsequent paragraphs:

For calcium, the estimation of coefficients was 0.00484 with a p-value of 0.129, indicating a statistically non-significant result. These results were compared with findings from Lake Victoria, where the estimation of coefficients for calcium was 0.9995 with a p-value of 0.9006, also showing no statistical significance. The reasons for these similarities in the non-significant results for calcium concentrations between the two studies are likely due to baseline calcium levels. The baseline levels for measuring calcium concentrations in both studies were consistent across both regions leading to small estimation of coefficients hence producing not statistically significant results. This could be due to lack of significant calcium-rich minerals in the geological formations of both areas.

In terms of electroconductivity, Urban Lake exhibited an estimation of coefficients of 0.6957 with a statistically significant p-value of 0.0031. In contrast, Lake Victoria showed an estimation of coefficients of 0.9999 with a p-value of 0.7901, indicating no statistical significance. These results differ due to the fact that several factors affect electrocon-

ductivity (EC) in different water bodies. Among these factors include sources of water feeding into the two Lakes. Urban lakes may receive significant amounts of stormwater runoff that carries various dissolved substances, increasing EC. Lake Victoria might have a larger proportion of its water coming from cleaner sources, such as upstream rivers with lower pollutant loads. The pH in Urban Lake had an estimation of coefficients of -0.7365 with a p-value of 0.7565, which was not statistically significant. This was compared to Lake Victoria data, where the pH estimation of coefficients was 0.9803 with a p-value of 0.1173; also demonstrating no statistical significance. The reasons for these similarities in the non-significant results for pH estimation of coefficients between Urban Lake and Lake Victoria are likely due to buffering capacity. Both water bodies may have similar buffering capacities, which stabilize pH levels despite the presence of acidic or basic substances. Natural buffering agents like bicarbonates, carbonates, and natural organic matter can mitigate significant pH changes.

For total alkalinity, Urban Lake got an estimation of coefficients of 0.0155 with a p-value of 0.6005, indicating no statistical significance. Similarly, Lake Victoria displayed an estimation of coefficients of 1.0002 with a p-value of 0.6431, also portraying no statistical significance. The reasons for the similarities in the non-significant results for total alkalinity between Urban Lake and Lake Victoria can be attributed by natural alkalinity levels. Both lakes might have naturally stable alkalinity levels that are not strongly influenced by the factors being studied. Natural sources of alkalinity, such as the weathering of carbonate rocks, can lead to consistent baseline levels that do not show significant variation.

Regarding total hardness, Urban Lake had an estimation of coefficients of -0.0438 with a p-value of 0.2042, indicating no statistical significance. In contrast, Lake Victoria displayed an estimation of coefficients of 0.964 with a statistically significant p-value of 0.0001. These results differ due to that several key factors can affect total hardness in Urban Lake and Lake Victoria differently due to geological differences. The geological composition of the watersheds feeding into the two lakes could be different. Lake Victoria might be situated in a region with abundant limestone or other calcium- and magnesium-rich rocks that consistently contribute to higher and more stable levels of hardness. Urban Lake might be located in an area with less of these minerals, leading to lower and more variable hardness levels.

Turbidity in Urban Lake demonstrated an estimation of coefficients of -0.0151 with a p-value of 0.5663, showing no statistical significance. Similarly, Lake Victoria displayed an estimation of coefficients of 1.0041 with a p-value of 0.3112, also exhibiting no statistical significance. The reasons for these similarities in the non-significant results for turbidity between Urban Lake and Lake Victoria can be attributed to several common factors like hydrological influences. Similar hydrological influences, such as inflow and outflow rates, sediment resuspension, and erosion patterns, might be at play

in both lakes. These hydrological factors can stabilize turbidity levels, leading to non-significant statistical findings.

In water analysis and assessment, a similar study was conducted in Lake Burullus and came up with the following findings:

In terms of discharge oxygen, the data from Lake Burullus indicated a p-value of 0.0001 which was statistically significant. However, looking at the data from Lake Victoria it shows a p-value of 0.284 demonstrating a no statistical significance. These results differ due to the fact that the environmental conditions and factors affecting oxygen levels in Lake Burullus and Lake Victoria are distinct. These distinctions are caused by hydrological characteristics. The hydrological characteristics, including water flow, depth, and volume of the lakes, are different. Lake Victoria is one of the largest freshwater lakes in the world, whereas Lake Burullus is a shallow coastal lake. These physical differences can influence oxygen dynamics [8].

Additionally, the total dissolved solids in Lake Burullus had a p-value of 0.0004, which is statistically significant. These findings were compared to those of Lake Victoria, which showed a p-value of 0.9163 for total dissolved solids which is statistically not significant. To account for these variations, we had to look at several factors influencing total dissolved solids (TDS) in the two lakes, including sources of pollution, in that, lake Burullus may have higher or more concentrated sources of pollution contributing to TDS, such as agricultural runoff, industrial discharges, or untreated sewage. These sources can introduce a variety of dissolved solids, including salts, organic matter, and chemicals, leading to a significant p-value. Lake Victoria, on the other hand, might have more diffuse sources of pollution or better regulation and management, resulting in less impact on TDS and a non-significant p-value.

Another factor to be looked at in the analysis and assessment of water quality was total suspended solids in Lake Burullus and the findings established that, the p-value for the analysis was 0.0005, which is statistically significant [8]. To compare these two studies there is a variation in that a p-value in which the p-value for water analysis and assessment from Lake Victoria was 0.9163 demonstrating no statistical significance. These results differ due to several key factors that can influence total suspended solids (TSS) levels in Lake Burullus and Lake Victoria. The causes for such differences could be geological and soil characteristics. The geological and soil characteristics surrounding the lakes can influence the number of suspended solids entering the water. Lake Burullus might be surrounded by more easily erodible soils that contribute higher TSS levels. Lake Victoria on the other hand, might have more stable soils that contribute fewer suspended solids [8].

## 5. Conclusions

The study concludes based on data obtained from the cen-

tral tendency and dispersion as well as those obtained from Multivariate linear regression model. The statistical measure of central tendency and dispersion gave us mean and standard deviation as output, whereas the multivariate linear regression model enabled us to get estimation of coefficients, 95% confident limit and p-value. The finding from statistical measure of central tendency and dispersion aligns with TBS and WHO standards (see table 1). Likewise, findings from the multivariate linear regression model agreed with WHO and TBS benchmarks (see table 2). Therefore, the findings from both statistical measure of central tendency and dispersion, and the multivariate linear regression model conclude that, the waters from Lake Victoria are suitable to human and animal needs, as well as to the environment. However, the current study suggests that: First, more data analysis using various computational approaches is needed in order to capture well different parameter values for the maximum assurance of quality of water all over the country. Secondly, the government should establish stringent monitoring procedures concerning quality of water issues that encompass seasonal patterns and require frequent reporting to the regulatory bodies such as TBS. Thirdly, the government should encourage innovation and research aimed at improving water quality systems. Furthermore, the government should promote and champion water conservation programmes throughout the country in order to ensure sustainability of water quality so as to reduce waterborne diseases such as cholera, dysentery and typhoid. Lastly, in the areas of further studies, the researcher suggests that, more studies should be conducted on water quality assessment based on TL since there is a limited literatures on this area.

## Abbreviations

Ca <sup>2+</sup>	Calcium
Cl <sup>-</sup>	Chloride
DO	Dissolved Oxygen
EC	Electrical Conductivity
Fe <sup>2+</sup>	Iron
Mg <sup>2+</sup>	Magnesium
pH	Potential of Hydrogen
SO <sub>4</sub> <sup>2-</sup>	Sulphate
TA	Total Alkalinity
TDS	Total Dissolve Solid
Temp	Temperature
TH	Total Hardness
TSS	Total Suspended Solution
Turb	Turbidity
TBS	Tanzania Bureau Standard
STD	Standard Deviation
WHO	World Health Organization
WQP	Water Quality Parameter
MLRM	Multivariate Linear Regression Model
TL	Tanzania Littoral
SAS	Statistical Analysis System

## Conflicts of Interest

The authors declare no conflicts of interest.

## References

- [1] Addisie, M. B. (2022). Evaluating Drinking Water Quality Using Water Quality Parameters and Esthetic Attributes. *Air, Soil and Water Research*, 1-8: <https://doi.org/10.1177/11786221221075005>
- [2] Ali, S. (2023). Clean Drinking Water and Future Prospective. *Pakistan Journal of Science*, 1-12: <https://doi.org/10.57041/pjs.v74i1.140>
- [3] Ashwin, K., Arulmozhi, S., A. Gopalan, P. Mageshkumar, Rangaraj, A., Panneerselvam, M. Luda., E. P. (2022). Correlation, Regression Analysis and Spatial Distribution Mapping of WQI for an Urban Lake in Noyyal River Basin in the Textile Capital of India. *Advances in Materials Science and Engineering*, 1-10: <https://doi.org/10.1155/2022/3402951>
- [4] Bartonova, A., Topalovic, D. B., Javanovic, M., Jovasevic, M., Davidovic, M. D., & Ristovs, Z. (2019). In Search of an Optimal in-field Calibration Method of Low-Cost Gas Sensors for Ambient Air Pollutants: Comparison of Linear, Multilinear and Artificial Neural Network Approaches. *Atmospheric Environment*, 640-658: <https://doi.org/10.1016/j.atmosenv.2019.06.028>
- [5] Ebron, J. G., Leon, R. I., Alejandro, A. D., & Amoranto, B. A. (September 2020). Computational and Numerical Modelling for Classification of Water Quality of Lake. *International Journal of Environmental Science and Development*, 425-431.
- [6] Eck, D. (2018). Bootstrapping for Multivariate Linear Regression Models. *Statistics & Probability Letters*, 141-149: <https://doi.org/10.1016/j.spl.2017.11.001>
- [7] Gupta, K. K., Khatri, P., & Gup, R. K. (2020). Assessment of Water Quality Parameters in Real-Time Environment. *SN Computer Science*: <https://doi.org/10.1007/s42979-020-00368-9>
- [8] Hassan, A., Samy, G., Hegazy, M., Balah, A., & Faithy, S. (2024). Statistical Analysis for Water Quality Data Using Anova (Case Study - Lake Burullus influent drains). *Ain Shams Engineering Journal*, 1-25: <https://doi.org/10.1016/j.asej.2024.102652>
- [9] Hellar-Kihampa, H., & Ndunguru, P. I. (2021). Physiochemical and Bacteriological Water Quality Parameters in Relation to Land-Use Practices at Rural Catchment, Mbinga District, Tanzania. *Tanzania Journal of Science*, 1282-1295.
- [10] Hyangya, B. L., Walumona, R., Pascal, M. M., Zabena, F. Z., Alunga, G. L., Kaningini, B. M. Kankonda. (2021). Physico-chemical Characterization of Littoral Water of Lake Kivu (Southern Basin, Central Africa) and use of Water Quality Index to Assess their Anthropogenic Disturbances. *World Water Policy*, 1-28: <https://doi.org/10.1002/wwp2.12059>
- [11] Machiwa, P. K. (2003). Water Quality Management and Sustainability: The Experience of Lake Victoria Environmental Management Project (LVEMP) Tanzania. *Physics and Chemistry of the Earth, Parts A/B/C*, 1-8: <https://doi.org/10.1016/j.pce.2003.08.032>
- [12] Malek, N. H., Yaacob, W. F., Nasir, S. A., & Shaadan, N. (2021). The Effect of Chemical Parameters on Water Quality Index in Machine Learning Studies: A Meta-Analysis. *Journal of Physics*, 1-15: <https://doi.org/10.1088/1742-6596/2084/1/012007>
- [13] Niyongabo, A., Zhang, D., Ziyuan, W., & Gu, Y. (2023). Water Quality Characteristics of Lake Tanganyika in Burundi and Lake Victoria in Uganda. *Water Practice & Technology*, 1756-1774: <https://doi.org/10.2166/wpt.2023.120>
- [14] Palyangco, J. C., Gamalinda, E. F., Seronay, R. A., & Jumanwan, J. C. (2020). Assessment of Macroinvertebrates as Bio-indicators of Water Quality in the Littoral Zone of Lake Mainit, Philippines. *Asian Journal of Biological and Life Sciences*, 371-378: <https://doi.org/10.5530/ajbls.2020.9.56>
- [15] Sarda, P., & Sadgir, D. P. (September 2015). Computation of Water Quality Parameters and Prediction Tool ANN for Modeling of Water Quality of Reservoir. *International Journal of Innovative Research in Science, Engineering and Technology*, 8906-8911: <https://doi.org/10.15680/IJIRSET.2015.0409086>
- [16] WHO. (2011). Guidelines For Drinking - Water Quality. 1-564.
- [17] Wondim, Y. K. (2016). Water Quality Status of Lake Tana, Ethiopia. *International Institute for Science, Technology and Education (IISTE)*, 39-51.
- [18] Xu, G., Zhang, J., Lu, K., Yu, K., Li, P., Shi, P., et al. (2019). Seasonal Changes in Water Quality and its Main Influencing Factors in the Dam River Basin. *Catena*, 131-140.