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Prediction of Water Pollution Quality of the Kangimi Reservoir Storage, Kaduna State

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ABSTRACT:
Water pollution occurred in natural stream and water storage facilities due to influences of anthropology and environmental inducements. This study aims at predicting pollutant quality of Kangimi reservoir storage. The study assumed homogeneity characteristics of water pollutants from the catchment by relating streamflow with pollutants concentrations to formulate a predicted power model with logarithm solution. Reservoir stages were measured for the periods of April, May, June, July, August and September 2023 with correspondent water sampling for quality characterization. The model was calibrated and verified using measured acquired monthly data. The reservoir stages ranged from 24.29 m to 28.34 m while streamflow values ranged from 13.4M m^3 to 43.1M m^3. The quality revealed the turbidity values ranged 10.5 to 13.01 NTU, TDS from 465 to 695 mg/l, Chloride ranged from 34.0 to 54.04 mg/l, NO_3 ranged from 52.52 to 65.2 mg/l, while BOD ranged from 5.23 to 6.95 mg/l. The statistical trend is upward direction as various slope values ranged from 0.065 to 0.229 with exception of chloride in downward trend value of -0.172. The power relationships indicated a strong value of R^2 ranged from 0.27 to 0.98. The model revealed the monthly pollutants delivery, enrichment, flushing and dilution process in the reservoir, the quality exhibition behavior chemodynamic. The maximum pollutants into the storage quality is from the month of June through September with predicted values ranged from 5.45 to 5.59 mg/l. Amongst the study conclusion is by recommended the use of the model for monitoring pollutants in Kangimi storage.

Keywords: *Catchment, Stream stage, Storage, Pollutants, Reservoir, Streamflow, Water quality*

I. INTRODUCTION

Water pollution occurred in most natural water storage reservoir as a result of operational generation of watershed activities either due to human or environmental inducements. According to Babur and Kara [1] the quality of water in a natural resource is critically related to climate, geology, and geomorphology and land use types of the watershed surrounded it. The well-known human activities such as fertilizer applications on agricultural land, land degradation due to erosion and mining fields, and unplanned human settlements in a watershed, have all been interacted with ecosystems to developed to a negativity effect on water quality of most reservoir [2, 3].

The above effects may be exacerbated by desertification, whether anthropogenic or climatic in origin [4]. Also, the gradual enrichment of reservoir waters with nutrients aroused from free-range cattle herding and wind breeze, leads to enhancement production of aquatic weeds and sediments deposition of organic materials originating from the water column after decaying plankton or littoral zones and decaying macrophytes, thereby become pollutants in water bodies.

Therefore, the potential pollutants loading, its source and prediction for water quality assessment of any open water body or water reservoir storages that are associated with the mentioned environmental problems to ensure good water quality standard is frankly inevitable. For the proper understanding of water pollution, the identity and nature of potential contaminants are paramount to sustain a good water quality.

The term water quality was developed to give an indication of how suitable the water is for human, plant, animal or industrial consumption, and is an accepted term widely used in multiple scientific publications and researches related to the necessities for sustainable water management. These water quality standards were governed by the quality parameters set by [6] and [7] which must be maintained to avoid the consequences on human or animal health.

Many Authors have studied water quality amongst of which are Islam [8], whose aim was to determined contaminant on nine (9) water quality parameters using Water Quality Index (WQI) for quality standard of Dhaka River. Yahaya *et al* [9] carried out the groundwater quality of four (4) Emirate zones of Kebbi State, Nigeria with the aim of determine the safety of well water because of primary dependents of the zones on groundwater.

In recent research by Abdulkareem *et al* [11] based on wet and dry season water samples analysis of Kangimi Reservoir Storage, the result showed that the water quality is unsuitable for direct drinking due to pollution relative to Nitrate (NO_3), Turbidity, Total Dissolve Solid (TDS), Chloride (Cl) and Bio-Oxygen Dissolve (BOD). This is obvious, perhaps, due to the pre-occupation of the catchment with cattle rearing and agricultural activities that have been in place leading to materials loading and eroding. There is need to formulate a prediction model for the existing pollutant parameters and future management of water quality of the Kangimi water storage reservoir. Hence, the research predicts and assesses change in the concentration of the pollutants due to the climate event and its behavior.

II. MATERIALS AND METHODS

Kangimi catchment features and streamflow characteristics

The Kangimi earth dam reservoir in Fig. 1 is showing sub-catchments network tributaries confined a volume of 59,789,001 m^3 of water by a spillway of 122 meters' width [12]. The dam was constructed across Kangimi River on approximately 3.22 km upstream confluence of Kaduna River [13] on the latitude and longitude of 10°46'N and 7°25'E, respectively, having surface area of about 12 km^2, 9.63 km long and maximum depth of 12.92 m [14].

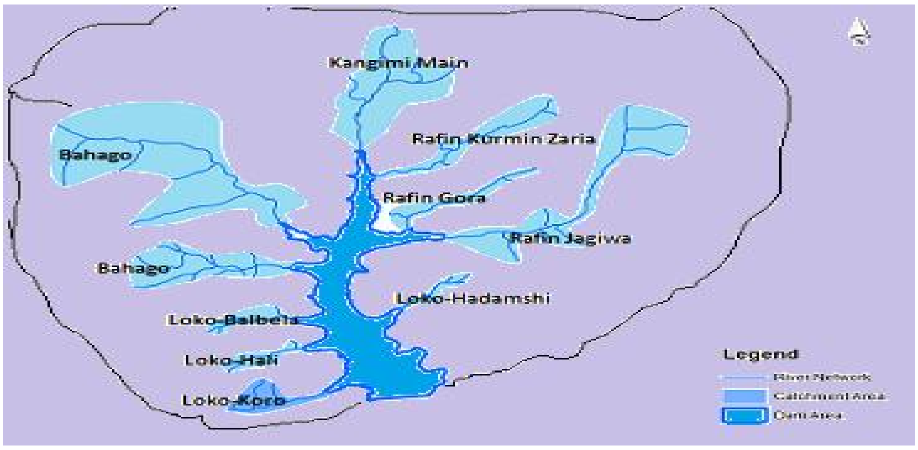

Fig.1: Kangimi dam showing sub-catchments networks

The catchment soil classifications are characterized by clay-loam to silt-clay-loam associated with high soil erodibility, moderate slope of between the highest values of 4.94 % and the lowest 0.0 % on the elevation of between 583.67 m to 673.19 m above sea level, of which the reservoir storage formed valley for surface runoff harvesting whenever there is storm. The major land use and land cover types are vegetation covered with an area of about 156.5 M m^2 (59.6%), farmland 38.97 M m^2 (14.83%), Waterbody 27.79 M m^2 (10.58%) [15]. The historical highest rainfall depth of the catchment was 1691.34 mm recorded in 1955 [16]. The other compared means depth is 1241.68 mm, with minimum and maximum values of 779.93 mm and 1636.30 mm, which occurred in the year 2000 and 2013, respectively [15]. The rainfall is characterized by moderate variability of (CV) value 0.195, synonymous to the Northern Nigeria rainfall distribution [17].

Prediction model formulation

Formulating model to predict a system of water pollution quality is a complex task, nevertheless, it has always been based on assumptions as no model supersede or better than any ones. Water pollution quality prediction may be focused on two important components, namely, predicting the pollution developments on a water-basin point and its consequent effects, and the second is predicting the changes in concentration of the pollutants when already in the stream.

Water body may receive pollutants from a point source or a non-point source. A point source defines the pollutants entering the water body from a well-defined outlet or locations as happens with municipal or industrial waste. While the non-point source is a key feature of any surface-water from the river/stream catchment or watershed, which is delineated by topographic, and all surface runoff within the watershed that have the potential to flow into the river or stream body.

Looking at non-point source load pollutants, it is hypothetical to say that the physical, biological and chemical characteristics of water contaminants from the catchment or watershed to the reservoir storage is linearly related to the catchment discharge. By homogeneous principle assumption with consideration of two or more pollutants constituents', the satisfying equation to relate this research problem solving is presented as Equation (1)

$$P_w(t) = C_1(t) + C_2(t) + C_2(t) + \ldots + C_n(t) \quad (1)$$

Where, $P_w(t)$ is the water pollutants in *mg/l* in a period of time and C_{1-n} indicates the concentration of each number of pollutants in water in *mg/l* in a period of time.

From Equation (1), it could be noted that the pollutant concentration constituents are directly proportional to the inflow discharge, *Q,* from the catchment which can easily be empirically represented and obtained by the point slope equation of a straight line Equation (2)

$$C_P = \beta Q + b \quad (2)$$

Where, Q is the streamflow discharge, m^3/sec, β is the intercept, and b is the slope gradient.

The representation curve in Eqn. (2) is developed using logarithmic transformation data with streamflow discharge as independent variable and pollutant concentration as the dependent variable. The solution is given using linear model of logarithmic transformation (Eqn. 3)

$$Log\,P_w(t) = LogC_1(t) + LogC_2(t) + LogC_2(t) + \ldots + LogC_n(t) \quad (3)$$

Equation (1) is valid with the assumption that there is seasonal flow having concentration characteristics of agricultural land in litres of water; the flow through catchment is homogeneous; and flow is directly proportional to the time period of the year, and considered higher than acceptable or permissible limit of [6] and [7]. By these assumptions, it means that pollutants loading into the reservoir are strongly controlled by the discharge, Q from the catchment.

Model verification and validation

Developers, users or decision makers of a model are always concerned with whether a model and its results are correct and represent the real-world using model verification and validation. Verification is often defined to ensure that the computer program of the computerized model and its implementation are correct, while validation in computer domain of applicability possesses a satisfactory range of accuracy and consistency [19]. To satisfy this condition in this work, two methods were observed namely: the secondary discharge data from [20] were collected and fitted into the model, and the statistics output compared.

Data collection and preparation

Data needed includes the water samples for the pollutant concentrations determination, the measure and primary data of the streamflow discharge for previous and current months of April, May, June, July, August, and September.

Water sampling and laboratory analysis

Collection of water samples for chemical and physical pollutants followed the standard procedure as slated and iterated by Meals *et al* [21]. Samples were collected from the reservoir storage into the polyethylene bottle after proper washing and cleaning with representative sampled water. Twenty (20) water samples at various points representing the upstream and downstream of the reservoir for the months of April, May, June, July, August and September 2023 simultaneous with reservoir stage measurements. The samples later reduced to ten (10) by mixing thoroughly in orders of 1 & 2, 3 & 4, …., 19 & 20 for each of the months for easy data handling, and transported to the Laboratory for analysis. The parameters analyzed for the sample concentrations were selected based on [1] report on the basis of Nitrate (NO_3), Turbidity, Chloride (Cl), Total Dissolve Solid (TDS) and Biological Oxygen Demand (BOD) and available funds. The results were subjected to statistical analysis to identify and satisfy the reliability of the data sets.

Collection and analysis of reservoir stream discharges

Average daily reservoir stages (m) data of 1993 – 2012 (secondary) were collected from KSWB. The stages for the months of April to September data of 2023 were observed, measured and recorded from Kangimi Dam Gauging station mounted by KSWB using expert staff of the Board. It has been applauded by Kuusisto [22] that more accurate values for discharge can be obtained when a permanent gauging station has been established on a stretch of a river or reservoir where there is a stable relationship between stage and discharge. The data measured was compared by visual examination with available data of same gauge of 1993 – 2012 to check for outlier values, measurement reliability and, to avoid exceeding or under recording of the stage values.

The datum adjustment for the purpose of correcting gauge-height values was made using Natural Geodetic Vertical Datum (NGVD) as explained by World Meteorological Organization [23] for which the datum constant for the research site is 579.12 m [20].

A rating table for the Kangimi dam from [14] was plotted on Microsoft Excel Spreadsheet 2016 which produced exponential best of fits. The rating curve is crucial because it allows the use of stream stage, which is usually easily determined to estimate the corresponding streamflow [24]. The streamflow discharge for various stages of each year was then generated from the exponential model which help to estimate stream discharges equivalent to the measured, observed and recorded months of April, May, June, July, August and September 2023 data stages.

Assessment of the propose model

In assessing a pollutant concentration using streamflow discharge against pollutant concentration, Pohle [25] chemostatic vs chemodynamic behavior of concentration against discharge. It has been adjoined to be a good strength by Porter [26]. Herndon *et al* [27] and Zimmer *et al* [28] defined the concentration export patterns to be chemostatic if $-0.1 \leq b \leq 0.1$, meaning concentration varied little with changes in streamflow discharge, and chemodynamic if $b > 0.1$ meaning that concentration varied significantly with stream discharge. The coefficient of variation, CV of the pollutants and streamflow discharge were calculated and evaluated, thus correlated for being low - 15.9%, medium - 68.3%, high - 13.6% and very high - 2.3% according to [29].

Also, the relationship strength is measured by the coefficient of determination (R^2) which measures how much of variation in solute concentration is explained by variation in streamflow discharge. Thompson *et al* [30] equation, CV_C/CV_Q, was used to provide a more robust assessment of what is occurring in the catchment by calculating the coefficient of variation (CV) of the solute concentrations and dividing it by the coefficient of variation of stream discharge, this measures the degree of chemostatic vs chemodynamic. Chemostatic behavior indicates a greater variability in the solute concentrations and that streamflow discharge of which is not the sole factor influencing concentrations.

Trend analysis

The objective of trend analysis in statistical terms is to identify if the values of the variable is generally increasing or decreasing over some period of time, as the trend in streamflow of hydro data series can be ascribed to variability [31]. Also, von Bromssen *et al* [32] buttressed that a trend can be observed in addition to a relationship between concentration and streamflow because if ignored such trends could influence the accuracy of slope estimation.

For this study, attempt was made to estimate the trends magnitudes and statistical significance of the trends in the average monthly streamflow for every pollutant using the power model provided in Eqn. (2) where trend is equal to slope of the line, *b*. This concept framework has been supported by Maher [33] and simply interpreted as change from increase (+ve) to decreased (-ve).

III. RESULTS AND DISCUSSION

Characterization of pollutants concentrations in water samples

Table 1 presents the average measured reservoir stages for April to September, 2023 with correspondent corrected datum level, equivalent streamflow values and the projected streamflow values from [18]. The mean solute concentration of the various targeted pollutants for the months of April to September were as well presented in the table.

The average daily measured reservoir stages as presented in Table 1 strictly reflected the original data from KSWB [20] of stream stages of Kangimi Dam Reservoir when compared and also, in line with NWRI [14] rating curve data. However, the fortunate implication here is that the stage can easily be related to the Olorunaiye *et al* [18] best line model that predicted streamflow decade groups. The maximum and minimum stages presented by Olorunaiye *et al* [18] were 27.88 m and 25.63 m, respectively, of which the values differed by 0.47 m to measured values of 28.35 m and 1.34 m from the measured values of 24.29 m. From these corrected stream stages in Table 4.1, it is obvious to say the measured stream stages matched with [14], [18] and [20] data series. This further demonstrated that the interpolation of the streamflow discharge with the measured stages will accurately estimate the current values as presented in Table 1.

The estimated mean streamflow discharges as showed in Table 1 for 2023 ranged from minimum value of 13.4M m^3 to maximum value of 43.1M m^3. The result suggested that, the present streamflow record is greater in maximum value when compare with 40 years' data presented in [18] and [14], though, the minimum value (13.4M m^3) exhibited lower value when compared with [18] (19.7M m^3).

From individual pollutant characterizations in Table 1, turbidity monthly average increases from the month of April down to September probably due to progressive surface runoff to the reservoir. The values ranged from 10.5 NTU (minimum) for April and 13.01 NTU (maximum) for the September. When these values were compared with mean, maximum and minimum values (9.05, 10.85 and 7.84 NTU), respectively, of [11], the current turbidity values (range 10.5 – 13.01 NTU) indicated higher than the acceptable standard of [6] and [7]. This further confirmed [11] study on the high turbidity trends on the Kangimi reservoir water storage. Though, this may not pose any health challenges to agricultural water use, but may be a harbor for entrapping heavy metals or microorganism as stressed by [7].

In the month of April, the mean TDS values ranged from 465 mg/l to maximum 695 mg/l at September. The values are slightly higher from the acceptable standard 500 mg/l of [6] and [7], though agreed with [11] wet season water sampling analysis report because of seasonal inflows from the predominant agricultural field of the reservoir catchment.

As chloride been highlighted among the pollution relative by [11], this current research results indicated the values range of 34.05 mg/l to 54.04 mg/l shown in Table 1, for the month of April and July which ranged between 45.91 mg/l and 54.04 mg/l, respectively. This shows that the concentration exported into the reservoir decreases or neutralizes as more flows increases since August and September values remained lower with 39.97 mg/l and 34.05 mg/l, respectively. Though, chloride does not pose any health risk according to [7], but when consume by cardiovascular patient [34] could be a health detrimental.

Nitrate (NO_3) concentration varied from early 1st two months (April and May) with 52.52 mg/l and 54.70 mg/l, respectively, and progressively increased in June and July with 61.05 mg/l and 65.21 mg/l, respectively, shown in Table 1.

Table 1: The mean monthly stage, streamflow and pollutants concentration

					Mean Conc.(mg/L)			
Month	Mean Measured Stage, (m)	Corrected mean stage, (m)	Equivalent mean Streamflow, (m^3)	Turbidity (NTU)	TDS	Chloride	NO_3	BOD
April	25.49	604.61	18,935,044.03	10.5	465	48.21	52.52	5.89
May	24.29	603.41	13,398,923.75	11.75	478	54.04	54.7	5.23
June	27.79	606.91	36,740,305.19	12.01	506	45.91	61.05	5.47
July	25.93	605.05	21,495,043.78	12.45	620	49.03	65.21	6.95
August	28.34	607.46	43,050,953.81	12.95	625	39.97	58.24	6.82
September	27.73	606.85	36,110,453.23	13.01	695	34.05	55.96	6.91

From August and September, the concentration dropped to nearly initial April and May to the values of 58.24 mg/l and 55.96 mg/l, respectively. This showed that the streamflow discharge does not depends on the nitrate concentration since July streamflow with highest concentration (49.03 mg/l) produced third lowest streamflow discharge (21.5 Mm^3) and the highest streamflow discharge (43.1 Mm^3) in August produced fourth lowest concentration (39.97 mg/l). This result demonstrated the complexity expressed by [26].

Also, on same Table 1, BOD concentration values were slightly higher than acceptable limit of 5.0 mg/l of [6] and [7], the values ranged from 5.23 mg/l to 6.95 mg/l. In the month of June, the concentration increased from 5.47 mg/l to 6.95 mg/l in July and later dropped below 6.95 mg/l. It was observed that the BOD concentration increment corresponds to increase in TDS concentration. This could suggest that oxygen demand in the reservoir storage within the months of July to September is progressively on the increase probably due to organic contents that are directly related to TDS and responsible for dissolve oxygen necessary for oxidation and biodegradation of organic compounds as reported in [35]. The BOD parameter is a very commonly used standard in water quality measurement with significance to the organic material present [11] of which when present above acceptable standard, the water is said to be polluted.

Pollutant-discharge power relationships and trends

The power relationships of various pollutant concentrations against streamflow discharge were presented in Table 2.

Table 2: Pollutant-Streamflow discharge relationships

S/No	Pollutants, C	Power Model	CV	Coeff of Corr., R^2	CV_C/CV_Q
1	Turbidity	$C = 10.605Q^{0.118}$	0.077	0.98	0.184
2	TDS	$C = 434.18Q^{0.229}$	0.167	0.85	0.398
3	Chloride (Cl)	$C = 54.024Q^{-0.173}$	-0.158	0.43	-0.375
4	Nitrate (NO_3)	$C = 53.793Q^{0.065}$	0.079	0.27	0.189
5	BOD	$C = 5.359Q^{0.128}$	0.125	0.50	0.298

From Table 2, the power model statistically revealed upward and downward slopes trends of which only the chloride as pollutant exhibited downward trend. The upward trends values ranged from 0.065 to 0.229 while the downward value is 0.173.

The used of slope values to described the chemistry behavior of the pollutants in streamflow has been observed by [27] and [28]. A pollutant exhibit chemodynamic behavior when the slope value is greater than 0.1 and less than is termed chemostatic behavior according to [27]. The study slope values revealed chemodynamic behavior which further confirmed the significant pollutants variation in the reservoir storage as described by [26].

Furthermore, the strength of the relationship using coefficient of correlation, R^2 proved that there are good relationships between the streamflow discharge and the pollutant concentrations as the values ranged from 0.27 to 0.98 (Table 2). Though, the chloride and nitrate exhibited weak relationships with values R^2 equal to 0.43 and 0.27, respectively, but in agreement with [26]. Thompson *et al* [30] described CV_C/CV_Q ratio as a robust statistical tool to assess the catchment interaction. The ratio values shown in Table 2 ranged from -0.375 to 0.398 of which TDS exhibited the highest value, 0.398, followed by BOD, 0.298, turbidity and NO_3 having equal value of 0.18, showing chemodynamic behaviors flushing patterns as the *b-coefficient >0.1*. The Cl is only pollutant that has b-coefficient negative value of -0.375. From this result, it could be concluded that there is significant interaction between the catchment and reservoir storage particles loading at Kangimi reservoir.

Model presentation, calibration and validation

Using the concept of equations (1), (2) and (3) the research model is presented by Eqn. (4).

$$Log(P_w) = Log(558.58) + 0.119LogQ_t + 0.229LogQ_{tds} - 0.173LogQ_{cl} + 0.066LogQ_{NO} + 0.128LogQ_{bod} \quad (4)$$

The model was calibrated using secondary daily stage of streamflow discharges data from [20]. Graphical techniques provide a visual comparison of simulated constituent data and first overview of model performance [36]; hence, the results of calibration and validation are presented in Fig. 2, Table 3, and statistical regression analysis output to further support the arguments.

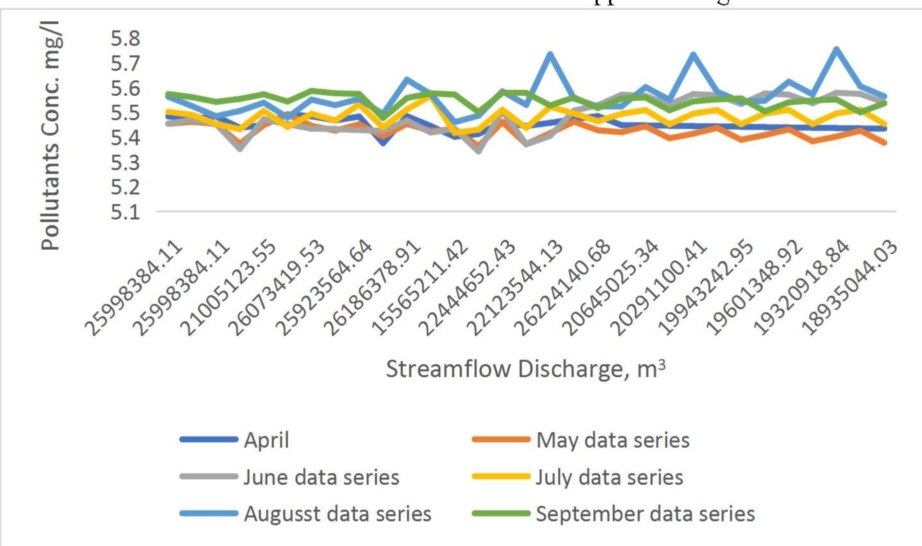

Fig. 2: Visual result of Model Calibration

Table 3: Descriptive Statistics of Model Predicted Daily-Monthly Data

Descriptive Statistics	April	May	June	July	August	September
Mean	5.45	5.42	5.49	5.48	5.56	5.55
Standard Error	0.0048	0.0057	0.013	0.0064	0.013	0.005
Median	5.44	5.43	5.47	5.49	5.55	5.55
Standard Deviation	0.027	0.032	0.072	0.036	0.072	0.028
Sample Variance	0.0007	0.001	0.005	0.0013	0.0051	0.0007
Range	0.17	0.13	0.24	0.15	0.29	0.11
Minimum	5.38	5.36	5.34	5.42	5.46	5.48
Maximum	5.49	5.49	5.58	5.57	5.75	5.59
Count	30	30	30	30	30	30
Conf. Level (95.0%)	0.009	0.012	0.026	0.013	0.026	0.010
Coeff. of Variation	0.005	0.006	0.01	0.007	0.01	0.005

From Fig.2, it was observed that the data predicted optimally at 5.75 mg/l in August of which predicted data series followed same patterns, though this does not necessarily affirm the good prediction or the accuracy of the model as other measurements are herein wait from the validation.

The pollutant concentration in April as revealed in Fig. 2 exhibited flat shape curve and almost to zero towards the month end. This probably exhibited distinctive low rainfall, hence, low inflow discharge and low dilution of pollutant concentration in the reservoir as it recovered from the prior natural and self-purification (dry season). The month of May pollutant concentration demonstrated variability as the curve exhibit clear up and down of which the mean concentration value is the lowest among the of the six (6) months. The months of April and May have the same behavior from the initial days as they overlapped each other (Fig. 2) and later separated, the condition suggests inflow discharge into the reservoir as rainfall progressively started. Also, May and June have equal concentration at initial streamflow as revealed in Fig. 2, but June later separated at the middle of streamflow discharge, and distinct self at upward direction to almost equalized with September pollutant concentration. The reason that could be suggests that rainfall at May was not severed and carried less pollutants, but with the climate characteristic of the study area, where moderate and excess rainfall begin to occur in June. The period carried more pollutants from the catchment surface into the reservoir and sustained the June pollutants concentration in an upward direction and eventually became among the highest as showed in Fig. 2.

The months of June equal other months with low pollutant concentration at the beginning as revealed in Fig. 2, but became among the highest as time progressed and rated second. It could be suggested that pollutants enrichment, flushing and dilution simultaneously took place as moderate and heavy rainfall begin to be experienced and more streamflow discharge is available into the reservoir. The months of July, August and September are more conspicuous among all the six (6) months in pollutant concentration delivery (Fig. 2). All the three months (July, August and September) exhibited a good surface runoff delivery as shown in Fig. 2 and varied as rain continued to fall, physically describing the chemodynamic nature of the reservoir and rainfall catchment surface washing as reported in [26]. From Fig. 2, it could be correctly to said that the month of July pollutants delivery is at moderate and could be the expected minimum pollutants delivery into Kangimi reservoir storage for the period of study. At this period the rainfall is steady, sometimes moderate in intensity, high intensity accompanied with thunder storm, and fall from time to time. This period could seriously be termed as Kangimi reservoir pollutants loading process and availability influenced by the rainfall and the physical state of the reservoir system. In the month of August, pollutants behavior can be described by flushing and dilution in the storage as the curve characteristics revealed in Fig. 2. The pollutant concentration showed the highest level of concentration and consistence patterns from the initial streamflow discharge, although, the month of September behaved similar, but differed by exhibited higher pollutants (5.75 mg/l) from the first 10^{th} days at moderate variation. For the month of August again, maximum pollutants delivery was observed (Fig. 2) and expected to remain till the rest of the raining days of the season if go by the seasonal period of Kangimi dam catchment. The month is so distinct and conspicuous as showed in Fig. 2.

Another interesting month is September pollutants concentration of the second highest concentration (5.59 mg/l). The probable reason could be that, the streamflow discharge with pollutants during the month of August remained in enrichment, dilution, flushing and mixing when the reservoir storage is preparing to receives both direct rainfall and surface runoff. At this period as showed in Fig. 2, month of September seized to move in upward direction on like the month of August probably due to the stoppage in rainfall within the period and which later reduced the stream discharge.

Furthermore, the model validation was performed and the result is presented in Table 3. The statistics means ranged from 5.42 to 5.56 mg/l of which the month of August has the highest mean with the value of 5.56 mg/l further reiterating the month's unique characteristics as previously described. The medians of the pollutants in all the months from Table 3 are closely equal with respective means and ranged from 5.43 to 5.55 mg/l. For data to be adjoined of good and standard accuracy, Novak [37] characterized the median not to be differed from mean by 0.20%, of which this study result revealed a good standard and accurate predicted data with general percentage value of 0.09 %.

Though, the values of means are closely equal, there is need for more information to substantiate the comparative analysis. The suggestion that needs to consider the standard error, standard deviation and sample variance as important. From Table 3, the standard error ranged from 0.005 to 0.013 at 95% confident level among of which months of April and September are more stable as their values are lower than others (0.005). This means that one can categorically say that the model prediction contains the average pollutant concentrations in the reservoir storage. Standard error is a goodness-of-fit that measure the precision of regression analysis, which measure the smaller the number the more certain the regression model. The standard error is an absolute measure that shows the average distance that the data points fall from the regression line. The maximum value of 5.75 mg/l was obtained in the month of August and the minimum value was 5.34 mg/l occurred in the month of June under the confidence level of 0.95 having the same standard error value 0.0013.

Sample range is another measure that shows the difference between the minimum statistic values and maximum values of the predicted data set. From Table 3, it could be observed that the samples ranged from 0.11 to 0.29. The smaller the value is the less variable is the data and therefore, the more desirable the model. When these values are subtracted from 1.0, the values approach unity and adjudged as desirable model, hence the model herein is desirable.

The presentation of descriptive statistics may not be enough to ascertained the relevancy or the significant level at which of the months do the concentration increases or decreases. The solution is statistics regression analysis and which is most paramount important and, hence the result in Table 4.

Table 4: Regression Analysis of the monthly predicted data

Months	Coeff. of Det., R^2	Intercept Coeff. value	Std Error	F-value	Significant F	t-Stat	p-value
April	0.98	5.285	0.0037	2053.72	9.54E-28	1421.20	1.45E-69
May	0.98	5.263	0.0037	2027.67	1.14E-27	1437.76	1.05E-69
June	0.96	5.320	0.0066	767.63	6.79E-22	809.69	1E-62
July	0.98	5.320	0.0043	1431.08	1.39E-25	1245.48	5.82E-68
August	0.93	5.450	0.0068	395.86	4.65E-18	802.43	1.29E-62
Sept	0.99	5.380	0.0029	3377.94	1.43E-31	1803.76	8.76E-75

The statistics output of the model monthly predicted in Table 4 revealed the strong capability of the model as the coefficient of determination, R^2 of all the months ranged from 0.93 to 0.98. This is evidence of degree of the dependent variable co-related with mean value of the predicted data, and for this model it is quite well related at confidence level of 0.05. The estimated intercept coefficient values (5.26 – 5.45) in Table 4 for all the months were within the average pollutant concentration values (5.45 – 5.56) when compared with the measured data set. Standard error is another goodness-of-fit measure that shows the precision of regression analysis of which the smaller the value the more certain about the regression model. From Table 4 it could be noted that the values ranged from 0.0037 to 0.0068, and almost approaching zero (confidence level of 0.05), which means that on average of 97% of pollutant concentration data fit the regression model and further supported by the range of R^2 values (0.93 – 0.99).

Furthermore, the model reliability was tested under the same regression analysis of which the significant F values ranged between 4.65E-18 – 1.43E-31 for all the months, confidently enough to say pollutant concentration were strongly and statistically significant at significant level of 0.00000 ($F<0.05$) (Table 4). Another indicator for effectiveness of the formulated model in this regression analysis is comparison of p-values generated for all the pollutant months. The estimated p-values, 1E-62 – 8.76E-75 under the low values standard error (0.0029 – 0.0068) with very strong coefficient of determination, R^2 (0.93 – 0.99) is less than statistical p-value. The statement means that model prediction of pollutant concentration is statistically significant at 0.05 and 0.01 (1E-62 – 8.76E-75) (Table 4). These results agreed with the report by Kendall *et al* [38] in which the overland flows and stream flows were 98% and correlated with stream chemistry of which the chemistry composition is a group of chemical elements that may be referred to as pollutants when it exceeds the [6] or [7] water quality standard.

IV. CONCLUSION

Water quality sample analysis has been characterized to ascertain the pollutant concentration relative to previous studies. The study identified turbidity, total dissolved solid (TDS), chloride (Cl), Nitrate (NO_3), and Bio-Oxygen Demand (BOD) as major pollutants that are higher using water quality index (WQI) on which this current study based its study to predict further the potential and behavior of the pollutants on the existing Kangimi reservoir storage.

The streamflow discharge for the period revealed the maximum and minimum values of 43.1M m^3 and 13.4M m^3, respectively, indicating the flows fell within the previous studies e.g. [14], [18], [39]. The pollutants characterization relative to turbidity, TDS and BOD concentration increase with increase in streamflow discharge, the condition that concludes the enrichment process in the reservoir, while chloride and nitrate are not stable as streamflow increases, the condition also suggests flushing and dilution for the climate season (rainfall in particular).

The study model revealed a good relationships strength between the stream discharge and pollutant concentrations as the coefficient of determination, R^2 ranged from 0.27 to 0.98. The model predicted turbidity, total dissolved solid (TDS), Nitrate (NO_3), and Bio-Oxygen Demand (BOD) in an upward trend, while chloride (Cl) was exceptional with downward prediction. This concluded that the later four (4) pollutants trailed chemodynamic behavior and chloride with chemostatic behavior.

Using the model on the acquired monthly stream discharge data for the months of April, May, June, July, August and September for the year 2023, the predicted data series followed same patterns, though, it cannot lead to conclusion. In an individual monthly basis, April distinctively exhibited flat shape and probably suggests the prior recovery from natural and self-purification process in the storage because of low or no rainfall, while in May, variability of pollutant concentration was observed. The month of June and July can be concluded to be period of pollutants enrichment, flushing, and dilution processes as streamflow discharge increases because of steady and moderate rainfall depth. In the months of August and September, pollutants were predicted at highest and revealed the maximum pollutants delivery and remain till the rest of raining days.

The applicability of this model could be best used in monitoring the annual level of pollutants relative to the parameters considered in this study as it affects the water quality of the Kangimi reservoir storage. This could in turn help to understand the management of sediments and runoff materials into the storage.

It can be concluded, that Kangimi reservoir storage received pollutant concentrations loading through the month of June to August when all parts of the reservoir have been saturated with enrichment, flushing, and dilution processes as demonstrated from the model prediction. Also, the model statistically predicted pollutant concentrations at significant level (0.05 and 0.01) and the stream discharge are 98 % correlated with reservoir chemistry (pollutants) that are best described by chemistry of chemostatic and chemodynamic nature of open stream storage.

B. RECOMMENDATION

Base on the conclusion above, the study therefore recommends:

i. The use of the model for water pollution monitoring, prediction and management guide at Kangimi dam reservoir relative to parameters.
ii. Heavy metals were initially included in the model formulation, but because of challenges of instruments and funds the study was restricted herein parameters.
iii. Climate is important in water quality prediction, therefore, this study only emphasized on raining season, it is important to extend the scope to dry season period to justify the climate contribution.
iv. Numerical model application study to the storage is ongoing by the authors.

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CONFLICT OF INTEREST

The research was jointly conducted and all decisions agreed upon by all the Authors, therefore no conflict of interest.

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