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A STREAMFLOW–WATER QUALITY MODEL FOR ASA RIVER IN CENTRAL NIGERIA

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Abstract: Asa River has a diminishing water quality which is currently insufficiently monitored and the available data are dispersed and insufficient to create management policies that are well–informed. Given this, this research sought to create a streamflow–water quality model that is adapted to the unique features and intricacies of the Asa River, Ilorin. Linear mixed effects models that integrate streamflow and water quality parameters to simulate the dynamic interactions within Asa River were developed using R package. The findings suggest that Asa River discharge (Q) follows a seasonal hydrological trend with September being its peak flow month and that variations in EC are linked to changes in Discharge while other water quality parameters do not exhibit significant relationships with streamflow. Linear mixed–effects model (Model 2) which includes random effects for different months demonstrated a better fit to the data than multiple linear regression model (Model 1) and it was selected because it was found to be a more suitable choice for explaining the variability in "Discharge" and exhibited a better predictive performance. This model is built on a unique dataset of Asa River and hence may not apply in other temporal or spatial situations.
Keywords: model, discharge, water quality, Asa River Ilorin

BACKGROUND OF STUDY

Life is in water (Hyun, 2018). Water is the second most important need for life to exist next to air (Omer, 2019). Water quality is most popularly defined as the physical, chemical, biological (Spellman, 2013) and organoleptic (taste–related) characteristics of water (Krishna, Jose, Jeeson, Ashok, & Suresh, 2022). Water quality is a measure of the condition of water relative to the requirements of any human need or purpose and/or one or more biotic species (Shah, 2017).

Streamflow, measured in m^3/s, refers to the volume of water flowing past a cross–section of a stream over a given period of time (Water Action Volunteers, 2023). Streamflow naturally varies over the course of a year. The amount of streamflow is important because very high flows can cause erosion and damaging floods, while very low flows can diminish water quality, harm fish, and reduce the amount of water available for people to use. Climate change can also affect streamflow in several ways (U.S. Environmental Protection Agency, 2016).

Sometimes, it is assumed that there are direct, linear relationships between changes in the streamflow regime and concentrations or loads which lead to speculative predictions that increasing trends in streamflow lead directly to higher loads or concentrations (Ockenden, et al., 2016; Rice, Moyer, & Mills, 2017; Rostami, He, & Hassan, 2018). In contrast, Murphy & Sprague (2019) argued that the relationship between water quality and streamflow trends is more nuanced, and hence presented a conceptual model and analytical approach to explore this relationship without undermining possible challenges. Concentrations at low stream flows are of utmost importance when pollution is primarily from point sources. However, for many non–point source pollutants, concentrations are positively associated with high streamflow.

Systematic changes in streamflow regime are most often due to natural or anthropogenic causes. Simple approaches to trend estimation like linear regression amongst others are sensitive to both types of streamflow variability and as such do not isolate the effects of human actions on water quality. Instead, these trend estimates usually reflects the combined effects of human actions and streamflow variability.

To assess and control the impact of water pollution, water quality models are crucial decision–support tools (Ríha, 2020). Simulating water quality requires model integration because it is uncommon for a single model to be able to replicate the necessary processes at the various scales and levels of complexity needed (Fu, et al., 2020).

Streamflow–water quality models are essential scientific instruments that are used to help manage water resources, forecast, predict and explain phenomena at various spatiotemporal scales when direct observation or experimentation is not feasible, not morally nor economically acceptable or both (Baffaut, et al., 2015). They are useful tools in determining the spatial and temporal distribution of pollutants in the water, assessing and forecasting pollutant transport, modelling and forecasting intricate processes in water ecosystems and accelerating decisions about how water quality will be changed. These processes are intimately associated with the characteristics of the water flow amongst others (Liu, 2018).

Most rivers in Nigeria are currently not sufficiently monitored and the available data are dispersed and insufficient to create management policies that are well–informed. These difficulties are exacerbated by the lack of a forecasting streamflow–water quality model for most, thereby inhibiting the ability of local authorities, environmental agencies and researchers to make proactive, data–driven and adaptive management decisions for maintaining the river's ecological integrity and guaranteeing a sustainable supply of water for the urban population. This research therefore seeks to develop a Streamflow–Water Quality Model that is adapted to the unique features and intricacies of one of such rivers, the Asa River as it flows through Ilorin Township in Central Nigeria.

DESCRIPTION OF THE STUDY AREA

Situated in Ilorin, Nigeria, the Asa River is an essential source of water for industrial, agricultural and residential uses (Ahamefule, et al., 2019). Nonetheless, worries over the river's declining water quality have been voiced recently (Akinwunmi, 2019). The Asa River's water quality has declined due to a number of human activities, including urbanization, industrial effluents and agricultural runoff. This has made the river unsafe for downstream consumption as well as detrimental to ecosystems (Solihu & Bilewu, 2022). Additionally, during rainy seasons in Ilorin, precipitation often falls as rain leading to changes in Asa River flows and most pollutants enter the water source via runoff and rapidly pollutes the receiving water body (Hou, et al., 2022).

Asa River originates from Oyo State and it passes through Ilorin, the Kwara State's capital city in Nigeria's North Central region (Ayanshola, et al., 2021) as illustrated in Figure 1. It is located between latitudes 8^{0}36′N and 8^{0}24′N and longitudes 4^{0}36′E and 4^{0}10′E in Ilorin and has many tributaries in the city. It flows in a South–North direction through the town (Balogun & Ganiyu, 2017). It is 302 ha in surface area (Ogundiran & Fawole, 2014). It is 56 km long from source at Ilorin.

The climate in Ilorin is humid, tropical, wet and dry climate (Ahamefule, et al., 2019). During high flows, the river stage is 2.9 m approximately and 60 m wide. Along the river's banks are residential, commercial, and agricultural structures. Asa River serves as a vital source of water for the city's economy, agriculture and environmental needs. Ritualists also perform rituals beneath the Asa Bridge and at the location of the dam site.

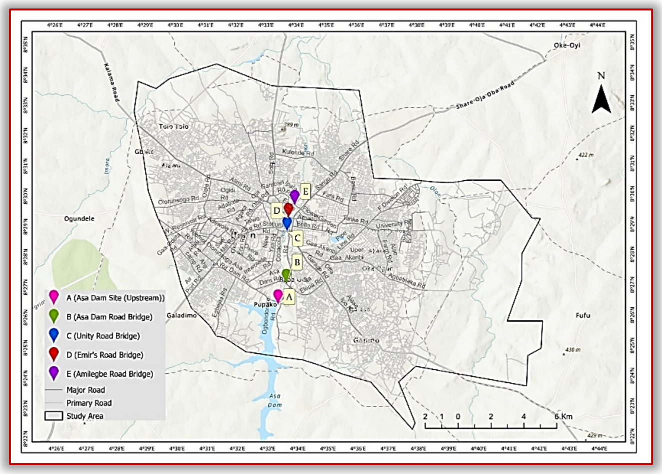

Figure 1: Map of Ilorin Metropolis showing Asa River course in Ilorin, Kwara State, Nigeria (produced by the author)

MATERIALS AND METHOD

Data Collection

Five locations along the Asa River were selected relative to the Asa Dam reservoir which is located naturally at the entrance of the river into Ilorin town. Careful attention was placed on choosing points close to anthropogenic activities. Discharge data was obtained from the conversion of catchment rainfall data of Asa River watershed. One year rainfall data for Asa River Catchment (which includes Ibadan, Ogbomoso, Oshogbo and Ilorin) was obtained from Nigerian Meteorological Agency (NiMET), and the water quality data was collected for one year which is the corresponding year of discharge.

Sterile water bottles were used to collect water directly from below the stream surface at each sampling location for seven months (covering both dry and rainy seasons) of the corresponding year of discharge. The temperature was immediately taken and then the bottle covered. The sample was immediately transported in a cooler containing ice packs to laboratory for analysis. The obtained water samples were subjected to microbial and physicochemical analysis. Standard Methods for the Examination of Water and Wastewater (America Public Health Association (APHA), 1995) was used for this analysis with results in duplicates. Water quality parameters tested for include: Total Dissolved Solids (TDS µs/cm), Electrical Conductivity (EC us/cm), pH, Turbidity (NTU), Biochemical Oxygen Demand (BOD mg/l), Dissolved Oxygen (DO mg/l), Nitrate (NO^{3-} mg/l), Sulphate (SO_4^{2-} mg/l), Chemical Oxygen Demand (COD mg/l), TOC (%), Phosphorus (P mg/l), Colour (TCU), Total Suspended Solids (TSS %), Total Nitrogen (N %), Alkalinity (mg/l), Temperature (°c), Arsenic (As mg/l), Chromium (Cr mg/l), Copper (Cu mg/l), Manganese (Mn mg/l), Nikel (Ni mg/l), Lead (Pb mg/l), Zinc (Zn mg/l), Cadmium (Cd mg/l), Calcium (Ca mg/l), Potassium (K mg/l), Sodium (Na mg/l), Magnesium (Mg mg/l), Total Bacteria Count (TBC x10^4 cfu/ml), Total Coliform Count (TCC x 10^2 cfu/100ml), Staphylococcal count(x10^3 cfu/ml) and Most Probable number (MPN/100ml).

Principal Components Analysis (Labrín & Urdinez, 2020) was used to analyze and reduce the dimensionality of the data. Consequently, four parameters that represents over 99% of the variance were identified. Missing values for the variables (EC, COD, Na, Alkalinity and Discharge) were addressed at this stage. Multiple Imputation by Chained Equations (MICE) was used to impute the missing values resulting in the creation of the complete dataset required for the Streamflow–Water Quality Model (Mera–Gaona, Neumann, Vargas–Canas, & Lo´pez, 2021; Roderick & Donald, 2020; Alruhaymi & Kim, 2021; Aisyah & Aszila, 2023). MICE Imputation is a sophisticated method for addressing missing data. It utilizes machine learning models to estimate missing values by considering other known data as predictors using bootstrapping approach (Kim, et al., 2022; Alruhaymi & Kim, 2021; Resche–Rigon & White, 2016; R Core Team, 2017). The method was iteratively applied multiple times similar to bootstrapping, by resampling the data and averaging the predictions. This approach enhanced data completeness by imputing missing values effectively. Continuous variables in the dataset including EC, COD, Na, Alkalinity and Discharge, exhibited some deviation from normality. To conform to the modeling assumptions required for the chosen statistical methods, a log transformation was applied to these variables. This transformation aimed to restore a more normal distribution to support the subsequent modeling processes.

Model Development

R package was used to develop Water Quality–Streamflow Model. Model Comparison was done using Chi–Test. Model Performance was judged for accuracy using statistical metrics (Mera–Gaona, Neumann, Vargas–Canas, & Lo´pez, 2021; Khan & Hoque, 2020).

RESULTS AND DISCUSSION

Table 1 represents the results of Principal Component Analysis. Eigenvalues listed in descending order represents the variance explained by each principal component (PC).

Table 1: Principal Component Analysis Result

Principal Component Analysis		
PC	Eigenvalue	% variance
1 (EC)	8074.73	82.509
2(COD)	1413.86	14.447
3 (Na)	157.91	1.614
4(Alkalinity)	82.15	0.839
5(Discharge)	39.51	0.404
6	15.04	0.154
7	1.73	0.017
8	1.18	0.012
9	0.28	0.002
10	0.11	0.001
11	0.02	0.000

The first four PCs in Table 1 explains 99.41% of the total variance. This means that EC, COD, Na and Alkalinity represented by PC1, PC2, PC3 and PC4 can adequately represent all the other parameters.

Relationship between Principal Water Quality Parameters and Flow

Table 2 shows the value of selected parameters for different months in the Asa River.

Table 2: Principal Water Quality Parameters and Flow for Asa River

Months	EC (us/cm) Mean Value	COD (mg/l) Mean Value	Na (mg/l) Mean Value	Alkalinity (mg/l) Mean Value	Discharge (Q m^3/s) of Asa River, Ilorin
Jan	451	342.0	1.86	6.86	0
Feb	453	340.0	3.86	6.87	0.01
Mar	450	240.0	2.99	6.89	4.58
Apr	445	140.0	2.68	6.97	4.36
May	441	96.0	137.19	7.11	12.81
Jun	342	152.0	2.01	6.58	17.04
Jul	240	150.0	1.51	7.12	10.11
Aug	218	139.6	1.82	42.00	4.89
Sep	185	218.0	1.64	6.543	27.89
Oct	133	104.0	1.47	39	20.60
Nov	122	102.0	1.35	6.95	0.09
Dec	110	100.0	1.25	6.85	0.00

Asa River discharge (Q) follows a seasonal hydrological trend with September being its peak flow (27.89m³/s) month. There is a clear seasonal pattern and a noticeable inverse relationship between EC and Q as well as COD and Q. The rainy season months with higher discharge tend to have lower EC and COD levels indicating improved water quality due to increased flow in the catchment and dilution of pollutants. There are however a couple of outliers in the data obtained which did not influence the main.

The elevated level in Na in May could be due to point source pollution events within the close proximity to Asa River. The fluctuations in alkalinity and discharge in the year suggest seasonal variations in water quality and flow regime. The months with higher discharge tend to have elevated alkalinity levels. This results from dilution of pollutants and neutralization of acidic pollutants that might have been discharged into the river via runoff or industrial chemical discharge into the river hence, increasing the water's buffering capacity. The observed elevation in alkalinity levels may also be suggestive of increased agricultural runoff within the catchment in August and October.

These suggests that monitoring and management efforts should be intensified during the dry season to mitigate the adverse impacts of high pollutants levels on water quality. Understanding these variations can help in the development of appropriate strategies for water resource management, pollution control, discharge limits, conservation efforts and maintaining water quality in the Asa Damsite Catchment.

Predictive Model for Streamflow–Water Quality

All analysis were conducted in R package. In the analysis, two models were developed and compared to study river discharge and assess their suitability for explaining the variability in the "Discharge" variable. These models include a multiple linear regression model (Model 1) and a linear mixed–effects model (Model 2).

— Model 1: Fixed Effects Model

Model 1 is a linear regression model that predicts "Discharge" based on the predictor variables: "EC," "COD," "Na" and "Alkalinity." It is specified as follows:

$$\text{Discharge} = \text{EC} + \text{COD} + \text{Na} + \text{Alkalinity} \qquad \text{(i)}$$

The results displayed in Table 3 shows that the intercept is 9.011 indicating the estimated Discharge when all predictor variables are zero. "EC" is significantly associated with "Discharge" ($p < 0.0001$) with a negative relationship suggesting that higher EC values are linked to lower Discharge. However, "COD," "Na" and "Alkalinity" do not exhibit significant associations with "Discharge." The model is statistically significant as indicated by the very low p–value ($p < 0.0001$). Model 1 offers a fixed–effects approach to predict "Discharge" based on the specified variables.

— Model 2: Random Effects Model

Model 2 is a linear mixed–effects model that introduces random effects accounting for variations across different months ("Months"). Including random effects for "Months" allows it to capture variations in "Discharge" between different months. It is specified as follows:

$$\text{Discharge} = \text{EC} + \text{COD} + \text{Na} + \text{Alkalinity} + (1\,|\,\text{Months}) \qquad \text{(ii)}$$

The results in Table 3 reveal that the intercept is 7.220 representing the estimated Discharge when all predictor variables are zero. "EC" is significantly associated with "Discharge" ($p < 0.0001$). However, "COD," "Na" and "Alkalinity" do not exhibit significant associations with "Discharge."

Table 3: Fixed Effects for Models 1 and 2

Fixed Effects for Models 1 and 2						
	Model 1			Model 2		
Variable	Beta	Standard Error (SE)	Pr(>|t|)	Beta	SE	Pr(>|t|)
Intercept	9.011	1.251	0.000	7.22	1.243	0.000
EC	–0.987	0.159	0.000	–0.814	0.155	0.000
COD	–0.185	0.159	0.248	–0.058	0.151	0.701
Na	0.130	0.064	0.044	0.102	0.069	0.142
Alkalinity	–0.282	0.120	0.021	–0.187	0.139	0.181

As observed in Table 4, the introduction of random effects enhances the model's ability to explain variations in "Discharge." The "Months (Intercept)" random effect has a variance of 0.2008 indicating that there are noticeable variations in Discharge between different months. The associated standard deviation (Std. Dev.) of 0.4481 signifies the typical magnitude of these month–to–month variations.

Table 4: Random Effects for Model 2

Random Effects for Model 2		
Variable	Variance	Std. Dev.
Months (Intercept)	0.2008	0.4481
Residual	0.6278	0.7923

The "Residual" category accounts for unexplained variability in Discharge. With a variance of 0.6278 and a standard deviation of 0.7923, it suggests that there is a considerable level of unexplained variation in Discharge that the model could not capture, possibly due to factors not included in the model or random fluctuations.

— **Model Comparison:**

The model comparison test (Chi–squared test) between Model 1 and Model 2 shown in Table 5 demonstrates that Model 2 significantly improves the model fit compared to Model 1 based on the lower values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for p = 0.001. In summary, Model 2 which includes random effects for different months provides a better fit to the data and is a more suitable choice for explaining the variability in "Discharge."

Table 5: Model Comparison

Model Comparison								
Model	Parameters	AIC	BIC	Log–L	Deviance	Chi–sq	Df	p–value
Model 1	6	319.66	336.38	–153.83	30766			
Model 2	7	310.72	330.23	–148.36	296.72	10.94	1	0.0009

Model Performance

The performance metrics for both models are summarized in Table 6. The coefficient of determination (R–squared) for Model 1 is 0.276, while the R–squared for Model 2 is 0.467. These values indicate that Model 2 explains a larger proportion of the variance in the data compared to Model 1. Also, the R–squared of 0.467 may be due to non–point source pollution of Asa River suggesting that the R–squared value could have been higher if it were a point source pollution. These results are for non–point source pollution samples. The performance metrics aligns with the model comparison results and supports the choice of Model 2 for its better predictive performance.

Table 6: Model Performance Metrics

Model Performance Metrics			
Model	R–squared (R^2)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)
Model 1 (Fixed Effect)	0.267	0.936	0.73
Model 2 (Random Effect)	0.467	0.865	0.698

Linear mixed effects models were employed to examine the relationship between streamflow (Discharge) and water quality parameters (EC, COD, Na and Alkalinity). The results revealed a significant negative relationship between EC and Discharge ($p < 0.001$) indicating that as Discharge increases, EC decreases. However, no significant relationships were found for COD, Na and Alkalinity in relation to Discharge. These findings suggest that variations in EC are linked to changes in Discharge while other water quality parameters do not exhibit significant relationships with streamflow. This also tends to justify the findings in Table 1 where the EC represents over 82% of the variance.

CONCLUSIONS

This study aimed at developing a Water Quality–Streamflow Model for the Asa River in Ilorin, Nigeria. The study reveals that Asa River discharge (Q) follows a seasonal hydrological trend with September being its peak flow month and that variations in EC are linked to changes in Discharge while other water quality parameters do not exhibit significant relationships with streamflow. Linear mixed effects models that integrate streamflow and water quality parameters (principal components) to simulate the dynamic interactions within Asa River were developed.

Model 2 which includes random effects for different months demonstrated a better fit to the data was selected because it was found to be a more suitable choice for explaining the variability in "Discharge." This choice was further strengthened by its better predictive performance and model comparison results. It will serve as a valuable tool for understanding the complex interactions between streamflow and water quality parameters and predicting the temporal and spatial variations in water quality within the river and for assessing the impact of anthropogenic activities on the water quality of Asa River.

This will also enable the formulation of strategies and policy development for effective water resource management, environmental science and pollution control in the study area. This study therefore suggests that other factors not considered in this model be explored in subsequent studies as they may influence the water quality parameters.

Application of Geographic Information System (GIS) for water quality monitoring and evaluation can also be explored.

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