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Application of QUAL2kw and Forecasting models for assessment of pollutants in upper Athi River catchment in Kenya

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ABSTRACT

Water pollution in the Athi river drainage basin, the fourth largest drainage basin in Kenya, has the potential of adversely impacting the aquatic biota and communities living downstream of the river. The upper part of the basin has experienced rapid industrialization in the recent past and there has also been increased encroachment of wetlands and forests for agriculture and settlement to cater for the increased population. The objective of this study was geared towards the generation of scenarios to predict future water quality trends in the upper parts of the Athi river basin. The prediction of the future water quality trends was undertaken in two phases: (i) the development of longitudinal water quality profile using QUAL2Kw model and (ii) prediction of the future water quality trends using the SPSS Forecasting tool. The collection of water quality data in established sampling stations located in the upper parts of the basin was carried out between January and December 2018. The archival data for the period 2015-2018 was obtained from Water Resources Authority (WRA) database for the determination of future trends in selected water quality parameters. The correlation analysis between the observed and predicted water quality parameters yielded strong R^2 values for temperature-0.82, electrical conductivity-0.99, total dissolved solids-0.94, biochemical oxygen demand-0.66, chlorophyll *a*-0.89, total nitrogen-0.75 and total phosphorous-0.94. The standard error ranged between 0.01-0.42, indicating that the model is reliable for predicting water quality parameters in the river. The available archival monthly data from 2015 to 2018 were averaged for time series forecasting to generate future water quality scenarios of the river for the period 2019-2030. The results showed that dissolved oxygen exhibit a decreasing trend in future indicating depletion of oxygen in water. There will also be significant increasing trends for Electrical Conductivity, Total Suspended Solids, Biochemical Oxygen Demand and Iron in future. There is a risk that the pollutants will increase to unsafe levels in the Athi River if appropriate management actions are not taken by the concerned agencies.

Keywords: Aquatic biota, Pollution, Prediction, Water quality, Watersheds.

INTRODUCTION

The degradation of water quality in the developing countries is unprecedently threatening the global water resources (UNEP, 2016). The sources of water pollution vary from place to place and normally include soil erosion, municipal sewage, agricultural chemicals and industrial effluent (Kithiia, 2012; Ochieng *et al.*, 2022; Uhlířová *et al.*, 2009). The pollutants adversely affect biodiversity, leads to the degradation and loss of ecosystems, creates health hazards, and reduces industrial capacity by increasing the costs of removing pollutants from the environment or through effluent/wastewater treatment. In many developing countries, this situation has been attributed to the increasing desire to achieve industrialization status (UNEP, 2016). Degradation of the river's water quality has been increasing in the recent past thereby adversely affecting the downstream communities relying on the river for various uses (UNEP, 2016). The upper parts of the Athi River basin have experienced rapid population increase and industrialization that has led to encroachment of wetlands and forests (Kitheka, 2019; Kitheka *et al.*, 2022). The diverse land use activities in the basin have been shown to contribute immensely to water quality degradation and pollution (Kithiia, 2012; Kitheka, 2019; Kitheka *et al.*, 2022).

The modeling of water quality in rivers and streams has been applied more extensively in developed countries than in developing nations (Bui *et al.*, 2019). In the USA, Hobson (2013) used QUAL2Kw as a Decision Support Tool for Silver Creek Watershed and found that modeling could be more cost-effective than the regular water quality monitoring. For instance, in Cértima River in Portugal, Qual2Kw model showed that the river was highly contaminated with high levels of nutrients (Hobson, 2013; Song *et al.*, 2020; Zhang *et al.*, 2012) although neither phosphorous nor nitrogen was limiting the proliferation of algal blooms (Schmidt *et al.*, 2019). QUAL2kw is a one-dimensional model with many applications, especially in river channels with non-uniform but steady flow with a roughly constant pollution loading (Chowdhury *et al.*, 2018; Flynn *et al.*, 2015; Ye *et al.*, 2013; Zhang *et al.*, 2015; Zhu *et al.*, 2015). In simulation, QUAL2kw factors in both the point and non-point pollution sources (Pelletier *et al.*, 2006). The usage of the model has been far and wide and there have been recent modifications of the model to allow for more robust simulation of rivers and streams water quality (Chaudhary *et al.*, 2018; Kalburgi *et al.*, 2015; Zhang *et al.*, 2014). A general mass balance equation is used to guide the model in the simulation of concentration within the water column (Santy *et al.*, 2020). The QUAL2kw model calibration process is geared towards determining model parameter values that best fit the modeled system (Yin and Seo, 2013). Both manual and automatic approaches are used to calibrate the Qual2Kw model. The manual calibration depends on the user's ability, and it's usually done by varying specific parameters, monitoring the final output, and repeating the process until the user is satisfied with the results (Abidin *et al.*, 2018; Cho and Lee, 2019; Rafiee *et al.*, 2014). On the other hand, the automatic calibration applies internal inbuilt algorithms, which are based on specific stoichiometry constants and rates (Nagisetty *et al.*, 2019; Zhu *et al.*, 2015). The automatic calibration optimizes the goodness of fit from the results of the model and compares data measured through the in-built algorithm (Hadgu *et al.*, 2014; Kamal *et al.*, 2020; Tang *et al.*, 2014). The in-built algorithm is the weighted average of the normalized Root-Mean Square Error (RMSE) of the variations between observed data and water quality parameters model predictions (Chen *et al.*, 2018; Xin *et al.*, 2019). The fitness function maximized by the genetic algorithm is given in the equation 1:

$$f(x) = \left\lfloor \sum_{i=1}^{n} w_1 \right\rfloor \left[\sum_{i=1}^{n} \frac{1}{w_i} \left[\frac{\sum_{j=1}^{m} O_{ij}/m}{\left[\sum (P_{ij} - O_{ij})^2/m\right]^{1/2}} \right] \right]$$

Equation 1

Where O_{ij} is observed data values, P_{ij} is the predicted values, w_i is the weighting factor, m is the observed and predicted values pairs, and n is the number of different parameters within the RMSE reciprocal. The detailed procedure of the QUAL2kw model calibration is well outlined by Pelletier *et al.* (2006). QUAL2kw system parameters required for calibration were obtained from existing literature and the model user manual (Zhang *et al.*, 2020).

Forecasting tools have been developed and designed to apply past happenings and present information regarding possible future scenarios of certain parameters (Fan *et al.*, 2021; Eskafi *et al.*, 2021; Sharma *et al.*, 2018; Katimon *et al.*, 2018; Abdeveis *et al.*, 2020; Babamiri and Marofi, 2021). Our present study on the forecasting of the future water quality trends was undertaken in the Upper Athi River basin in Kenya whose headwater streams such as Mbagathi, Nairobi, Ngong and Mathare drain areas with varying land use activities. The prediction of the future trends was undertaken in two phases, that is longitudinal water quality profile which was carried out using QUAL2Kw model, while the second phase of predicting future water quality trends was performed using the SPSS Forecasting tool. The objective of the study was to generate scenarios to predict future water quality trends in Athi River by utilizing the quantitative technique in simulation of water quality parameters due to its minimal errors compared to qualitative forecasting.

STUDY AREA

In Kenya, Athi River drainage basin (Figure 1) is considered the fourth largest drainage system with a total surface area of 69,930 Km^2 (Kitheka, 2019). However, the upper Athi River where this study was done has surface area of about 6799 Km^2 which is equivalent to about 9.7% of the total basin area (GIS & Survey of Kenya, 2016). The river originates from Central Kenya highlands especially the Ngong Hills, Kikuyu Escarpment and southern parts of the Aberdare ranges. The upper section of Athi River basin in the Kenya Highlands is densely populated with approximately 200–300persons/km^2 with intensive crop cultivation dominating the area (CWWDA, 2012). Major crops cultivated here include various horticultural crops, coffee and tea (Prasol Training and Consulting Ltd, 2012). The main tributaries of Upper Athi River include Nairobi River, Ndarugu, Mbagathi, and Ruiru rivers (Figure 1). Most of the rivers especially Nairobi River and tributaries (Mathare, Ruiruaka and Kamiti) traverses densely populated areas within Nairobi metropolitan area with varied anthropogenic activities such as commercial, industrial, informal settlements, agricultural, deforestation, solid waste disposal, wetland and riparian encroachment (Kitheka *et al.,* 2022).

The convergence of the Northeast and Southeast monsoons within the inter-tropical convergence zone causes biannual rainfall seasons in the basin (Ojany and Ogendo, 1986). The Northeast monsoon (NEM) often occurs between early March and October while Southeast monsoon (SEM) is pronounced between mid-September and mid-March. In the Upper Athi River basin, rainfall ranges between 1000 to 1200 mm per year, with the exception of La-Nina and El-Nino partially caused by inter-annual variations in rainfall. The air temperature in the Central Kenya highlands, which is the origin of the river, ranges between 18°C and 28°C, while in the semi-arid middle region of the basin the temperature varies between 20°C and 32°C (Ojany and Ogendo, 1986). The Central Kenya highlands experiences evaporation rates varying between 1200 and 1500 mm per year, while in the semi-arid lower region of the basin, the evaporation rates is approximately 1800 mm per year, which is remarkably higher than the yearly rainfall (Ojany and Ogendo, 1986). Therefore, water deficit is pronounced in the Athi basin during the dry seasons of the year.

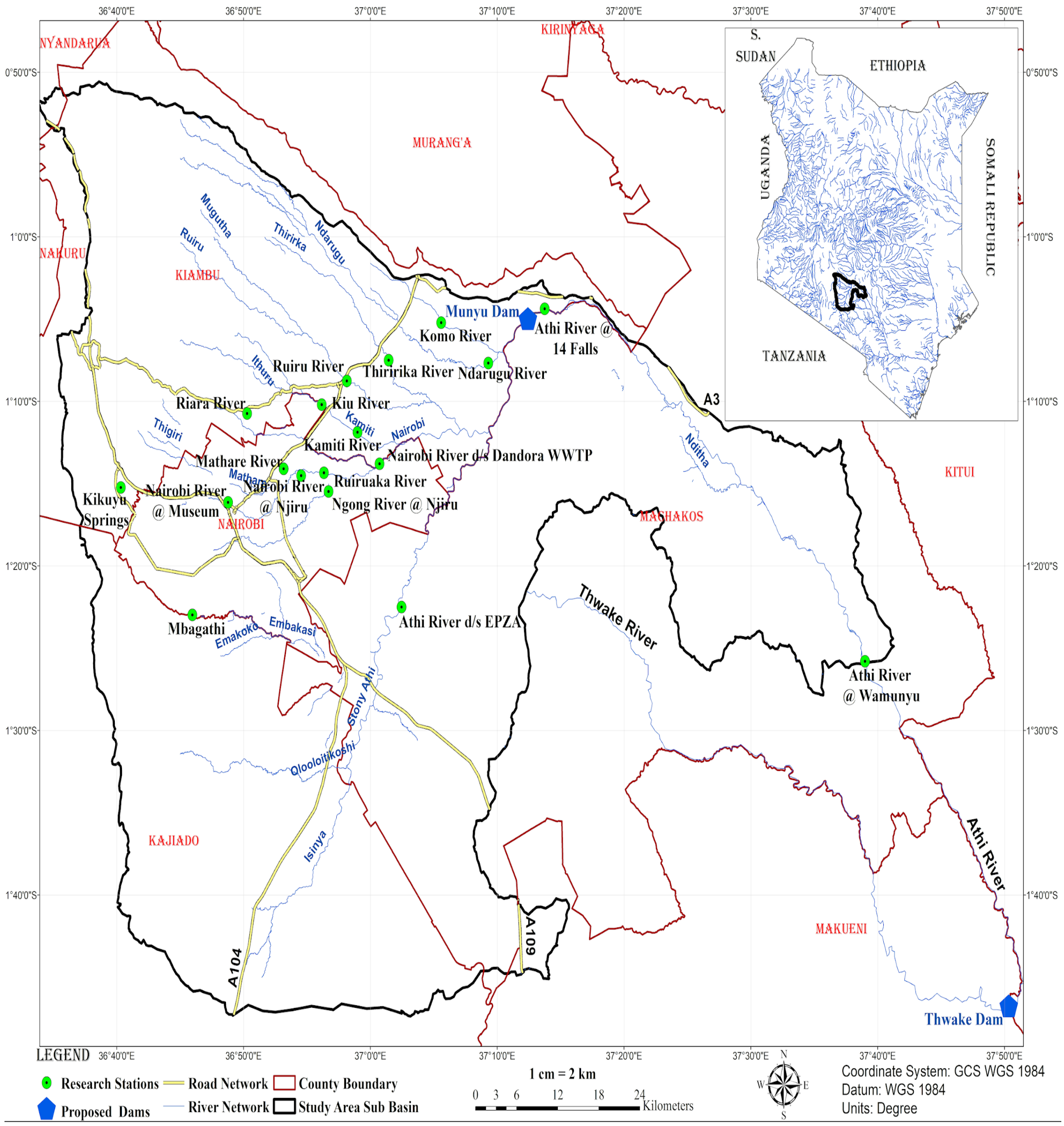


Figure 1: Map of the study area showing the location of Upper Athi River basin in Kenya and the research stations (Source: KE-CWWDA, 2021).

METHODOLOGY

Sampling

The study established 18 sampling stations along the main Athi River and its tributaries in order to determine the spatial distribution of concentrations of key water quality parameters. However, only 4 sampling stations along the Athi river stretch were considered for the modeling. The data collection was done between January to December 2018. In-situ field measurements were undertaken for Water pH, temperature, dissolved oxygen and electrical conductivity using a portable multiparameter meter (Model: H1 9828 HANNA instruments) supplied with multi-sensor probe. The probe was immersed into the river water to a depth of about 0.3m and the reading allowed it to stabilize, then pH value of the water was read and recorded. Similarly, temperature, dissolved oxygen and electrical conductivity were also measured.

Water samples were collected using 500ml plastic bottles for further laboratory analyses for the water quality parameters, Biological Oxygen Demand (BOD) and Total Suspended Solids (TSS). Total Nitrogen (TN) and Total Phosphorous (TP) samples were collected in amber glass bottles. Sampling for chlorophyll *a* was done in bottles covered in aluminum foil to avoid light penetration and further reaction. All samples were stored in a refrigerator at 4°C prior to analyses (APHA *et al.*, 2012) and whenever possible, analyzed immediately. River discharge data was obtained from Water Resources Authority (WRA) of Kenya.

QUAL2Kw methodology

QUAL2Kw tool was used for modeling by in-putting the physicochemical variables. Four research stations established along Athi River namely; Mbagathi Station, Athi River downstream EPZA Wastewater Treatment plant, Athi at Fourteen falls, and Athi at Wamunyu were used for modeling. The modeled stretch had a total length of 152 Km and was divided into four sections of varying lengths, which were mainly dictated by the position of the research stations. The Headwaters of Athi river are Mbagathi and Kikuyu springs. The Kikuyu springs are the source of Nairobi River, the main tributary of Athi. The springs are protected and are a water resource for the city of Nairobi, hence Mbagathi headwaters was used for the Qual 2Kw model because of its natural status.

Forecasting methodology

In the present study, the monthly data for the period 2015-2018 were averaged for modeling and forecasting. The excel forecasting feature Exponential Triple Smoothing (ETS) function was used to fill the missing data for the actual stations. The graphs generated future scenarios with upper, average and lower values. The line of best fit explained the predicted values. The observed monthly data for the period 2015-2018 was used to predict the monthly data for the period 2019 -2030 (Abdeveis *et al.*, 2020). The SPSS version 21 was used for data analysis in which the updated trends package offers automation for the most optimal model from each class depending on several performance measures (Attanayake and Perera, 2021). The water quality data for BOD, chloride, COD, DO, EC, Iron, pH, TDS, temperature, TSS and turbidity were obtained for years 2015 to 2018. The years 2017 and 2018 had all the monthly data available. Years 2015 and 2016 had data gaps which was filled using Linear Forecasting tool in excel. Long or increased historical data period, increases the error and have significant effect on the general scenarios (Nair and Sarin, 1979). An effective forecasting of data requires at least 3 years set of constant data and therefore the four set of years were chosen for an effective forecasting and optimal minimization of errors.

Calibration of QUAL2Kw model

The objective of model calibration was to determine the values for the model parameters that suits the QUAL2Kw model. The QUAL2Kw data was simultaneously organized for model calibration as well as validation. The model was calibrated using monthly average data for the dry season (December, January, and February) and validation was performed using monthly average data for the wet season (March, April, and May). For this study, the model was auto-calibrated using observed dry spell water quality data.

Relationship between river discharge and water quality parameters

The relationship between river discharge and water quality parameters such as correlation and regression analyses were determined with an objective of determining the accuracy of the model in forecasting the actual measured water quality data. To determine the relationship between river discharge and the water quality parameters, correlation analysis was undertaken in R (Version 3.6.0, R Development Core Team, 2019) vegan package (Oksanen *et al.*, 2019). To determine whether discharge variable could explain the variation in physicochemical parameters, linear regression analysis was performed in R (Version 3.6.0, R Development Core Team, 2019) vegan package (Oksanen *et al.*, 2019). The standard deviations, means, minimum and maximum values were computed using Excel Stat.

RESULTS

Longitudinal distribution of the water quality parameters

Even though, the available rainfall data was scanty and could not be analyzed, previous studies in the Upper Athi River basin demonstrated that the rainfall in this basin is highly variable having both seasonal and inter-annual variations, usually ranging from 481 to 1764 mm/year (Kitheka *et al.*, 2022). Further, the evaluation of rainfall data between 1981 and 2019 revealed significant inter-annual variability with a pattern of a declining rainfall coupled with increasing temperatures, thus emphasizing that the basin is under the influence of global climate change (Kitheka *et al.*, 2022). The high amounts of rains in the years 1988/1989,1987/1988 and 2017/2018 was attributed to the El Nino Southern Oscillation (ENSO) events (Ndomeni *et al.*, 2018). However, the period 2012-2015 experienced relatively low rainfall in comparison to 2016-2018 which received higher rainfall.

There was a remarkable longitudinal distribution of the water quality parameters in the upper Athi River basin. Temperature increased as the distance increased from Athi at Wamunyu (40.8km) to Athi at EPZA (140km) upstream and this station had the highest temperature of 24 ^{0}C (Figure 2F). EC results from the calibrated data had similar trend along the river stretch just like the temperature (Figure 2D). TSS decreased downstream along the Athi River stretch and the lowest level was recorded at Wamunyu with a value of 20 mg/l (Figures 2, A-I).

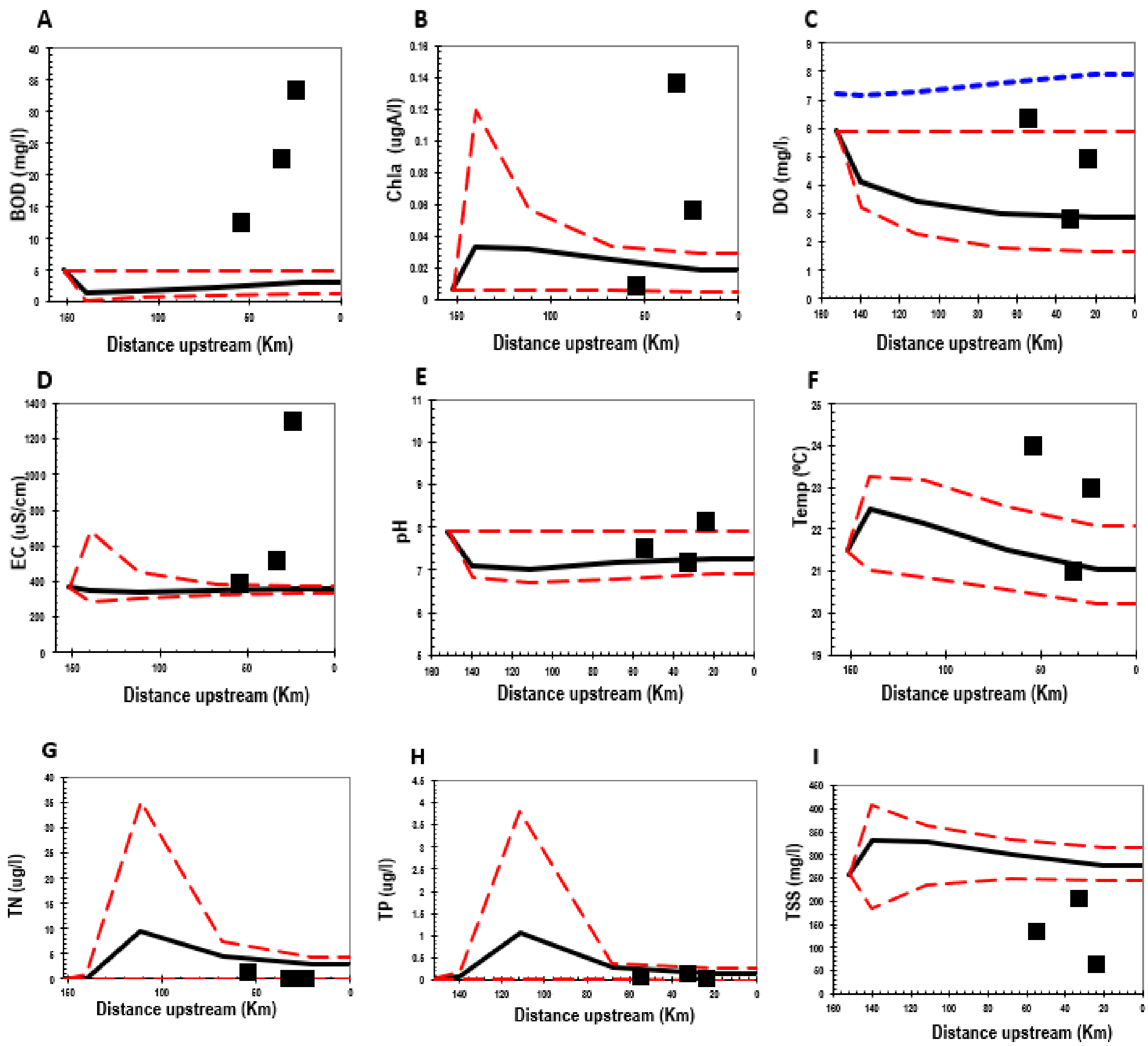


Figure 2 (A - I): The QUAL2kw calibration graphs of physicochemical parameters sampled from Upper Athi River basin.

Model validation

The model validation was carried out according to Attanayake and Perera (2021). The results showed that the validated graphs differed remarkably from the calibrated results (Figure 3, A-I). The validated results were more conspicuous with reference to the observed results from the sampling points. The BOD, chlorophyll *a* and the nutrients (TN and TP) showed similar trends along the river stretch (Figures 3G & 3H). The concentration increased downstream from Mbagathi (head waters) with BOD (Max, Min and average of 5.0mgO_2/l) to Wamunyu (the last downstream station of the present study area) with Max, Min and average BOD of 19.680mgO_2/l. Chlorophyll *a* for Mbagathi station was the same value 0.006mg/l for Max, Min and average, but for Wamunyu, Max-0.057, Min-0.05 and average was 0.051mg/l. Total Nitrogen and Phosphorous for Mbagathi were also similar 0.048mg/l and 0.03 respectively. Prediction of TN and TP for Wamunyu was (TN: Max-1.09mg/l, Min-1.07mg/l, and TP: Max and Min-0.138mg/l).

The observed water quality variables were compared with predicted values for the calibration and the validation runs. The results for water temperature, EC, TSS, BOD, TN, TP, chlorophyll *a* and pH were subjected to regression analysis. The largest disparity in results observed during the calibration period was with EC, with a standard error of 6.75 and R-squared value of 0.99. The TP had R-squared value of 0.93 and a standard error of 0.01. During the validation period, out of all the selected water quality parameters, non-presented a standard error greater than 1.0. The computed values were in the range of 0.01 – 0.42 and R-squared values in the range of 0.66 – 0.99. Hence, the validated data agreed very well with simulated data. The consequent R-squared and standard error values computed are presented in table 1.

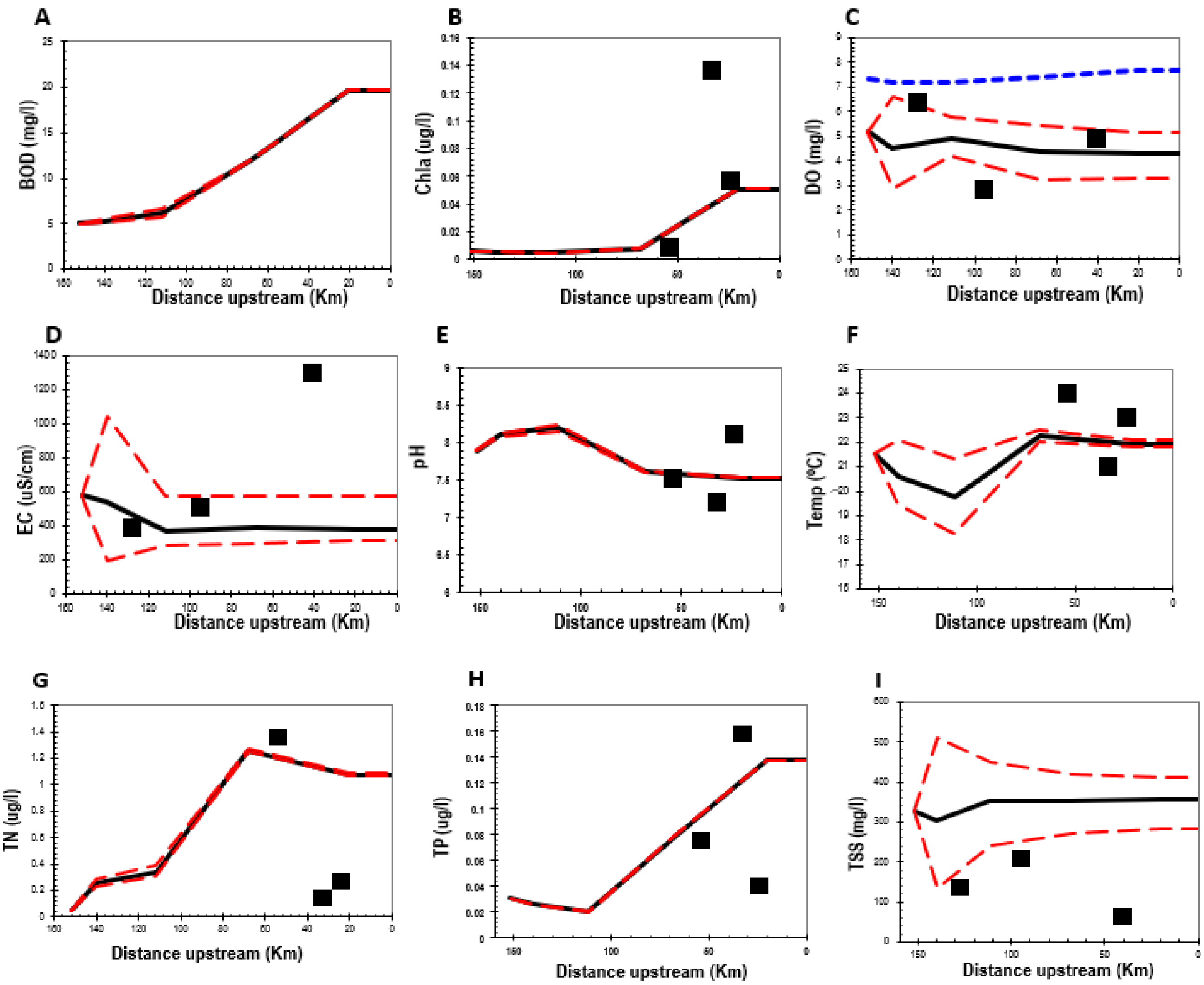


Figure 3 (A - I): The QUAL2Kw validation graphs of physicochemical parameters sampled from upper Athi River basin.

Table 1: R-squared and standard error for calibrated and validated water quality data from upper Athi River.

	Calibration		Validation	
	R Squared	**Std. Error**	**R Squared**	**Std. Error**
Temperature	0.88	0.47	0.82	0.34
Electrical Conductivity	0.99	6.75	0.99	0.42
Total Suspended Solids	0.97	4.25	0.94	0.06
BOD_5	0.88	5.44	0.66	0.30
Total Nitrogen	0.70	0.04	0.75	0.11
Total Phosphorous	0.93	0.01	0.94	0.01
Chlorophyll *a*	0.97	0.03	0.89	0.02
pH	0.98	0.13	0.99	0.11

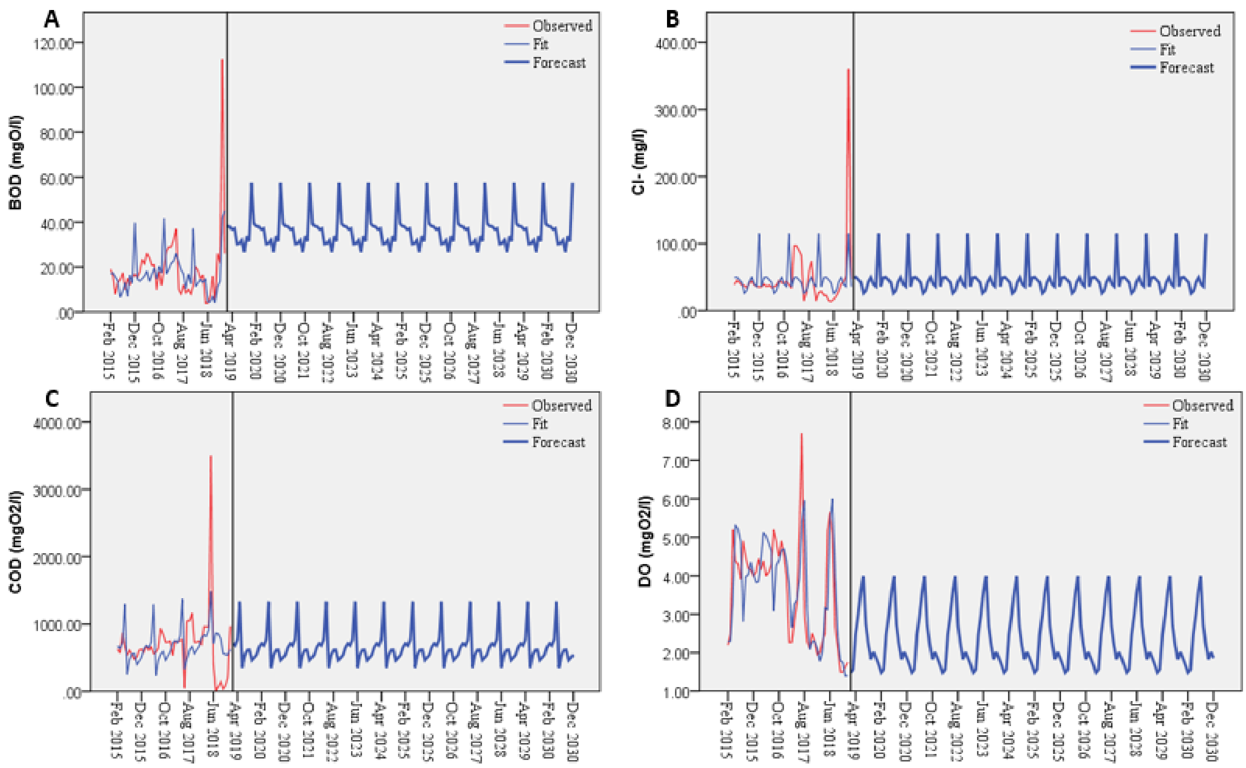
Comparison of the observed/measured and simulated physicochemical parameters

The Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are all used in linear regression to minimize the prediction errors of all the data points (Saigal and Mehrotra, 2012). The closer the value of MAE to 0 the better, while RMSE values between 0.2 and 0.5 reveals that the model is relatively robust to predict the data accurately. On the other hand, MAPE > 50 % is considered as good for prediction.

In the present study, comparative results for monthly sum of BOD between the observed and predicted BOD showed seasonal fluctuations (Figure 4), with means of 18.78mg/l and 31.30mg/l respectively (Table 2). The test results of the model revealed that; MAE = 8.61, RMSE = 14.02, and MAPE = 50.38 (Table 2), indicating average model performance for the estimated variables and depicted less confidence to the application for the predicted variables. The sum of monthly chloride concentration between the observed and predicted values followed a linear trend for both periods, with a peak in November (Figure 4). The observed and predicted chloride averages were 47.28 and 47.00mg/l respectively (Table 2). The test results for the model revealed MAE = 22.11, RMSE = 45.34, and MAPE = 52.34 (Table 2), an indicator of poor model performance. For the COD, the results of observed and the predicted values showed relatively parallel fluctuations (Figure 4), with means values of 688.51mg/l and 657.69mg/l respectively (Table 2). The test results of the model revealed; MAE = 295.13, RMSE = 455.78 and MAPE = 218.06 (Table 2), indicating model poor performance and low confidence in application and reliability of the predicted values. DO results show great variation between the observed and the predicted values (Figure 4), with a means of 3.61mgO_2/l and 2.68mgO_2/l respectively (Table 2). The test results for the model revealed; MAE = 0.688, RMSE = 0.994, and MAPE = 18.8 (Table 2), depicting reliability of the predicted variables. EC results showed relatively linear trend for observed EC, but fluctuations for predicted EC (Figure 4), with a mean of 693.1 and 401.5 µS/cm respectively (Table 2). The test results of the model revealed; MAE = 169.6, RMSE = 229.9 and MAPE = 33.1 (Table 2), which raises concern over the estimated variables. For Iron, the results of observed and the predicted values showed fluctuations with similar trends (Figure 4) and with a mean of 6.82mg/l and 11.02mg/l respectively (Table 2). The test results of the model revealed; MAE = 5.95, RMSE = 10.75, and MAPE = 169.94 (Table 2), thus an indicator of the reliability of the predicted variables. Our results showed slightly lower pH value for predicted values in relation to observed values (Figure 4), with a mean of 7.49 and 7.37 for observed and predicted pH respectively (Table 2). The test results for the model revealed; MAE = 0.295, RMSE = 0.372 and MAPE = 4.023 (Table 2), which gives great confidence to the application of the predicted variables. Comparative results of monthly TDS between observed and predicted, showed seasonal variations for observed TDS and relatively linear trend for the predicted (Figure 4), with a means of 398.89mg/l and 394.58mg/l for observed and predicted TDS respectively (Table 2). The test results of the model revealed; MAE = 94.56, RMSE = 130.02 and MAPE = 36.28 (Table 2) which lowered the confidence of the predicted variables. Temperature values showed relatively linear trend for the observed and predicted, but both had slight fluctuations (Figure 4), with means of 23.92 and 22.99 respectively (Table 2). The test results of the model revealed; MAE = 1.49, RMSE = 1.92 and MAPE = 6.29 (Table 2) indicating a good model performance and give confidence to the application of the model for the variables. TSS results between the observed and predicted showed general fluctuations (Figure 4), with a means of 163.67mg/l and 96.96mg/l for observed and predicted values respectively (Table 2). The test results revealed; MAE = 69.74, RMSE = 107.63 and MAPE = 78.56 (Table 2), which lowers confidence in applying the predicted variables. The comparative results of monthly sum of turbidity between the observed and the predicted values showed seasonal fluctuation (Figure 4), with means of 81.32 NTU and 82.28 NTU respectively (Table 2). The test results of the model revealed; MAE = 41.27, RMSE = 65.87 and MAPE = 68.54 (Table 2), which revealed relatively poor model reliability over the estimated variables.

Table 2: Model descriptive statistics of the physicochemical parameters in upper Athi River basin.

	Developed Model	Min	Mean	Max	Stdev.
EC (µS/cm)	2015 – 2018	135.2	693.1	1150	276.2
	2019 – 2030	14.4	401.5	1214.8	244.2
Chloride	2015 – 2018	14	47.28	360	49.4
	2019 – 2030	26	47	115.1	21.8
DO (mg/l)	2015 – 2018	1.5	3.6	7.7	1.4
	2019 – 2030	1.4	2.7	6	1.1
pH	2015 – 2018	6.1	7.5	8.1	0.5
	2019 – 2030	6.7	7.4	8.2	0.3
TSS (mg/l)	2015 – 2018	20	163.7	552	133.2
	2019 – 2030	76	97	552	94.4
BOD (mg/l)	2015 – 2018	4	18.8	112.5	15.6
	2019 – 2030	4.3	31.3	57.5	11.4
Fe (mg/l)	2015 – 2018	0.4	6.8	86.7	13.2
	2019 – 2030	5	11	40.2	7.7
COD	2015 – 2018	116.8	688.51	3500	493.69
	2019 –2030	237.98	657.69	1489.36	239.83
TDS	2015 – 2018	83.2	398.89	706.85	152.31
	2019 – 2030	225.45	394.58	564.4	41.6
Temp	2015 – 2018	18.4	23.92	28.98	2.37
	2019 – 2030	18.2	22.99	27.26	1.44
TURB (NTU)	2015 – 2018	12.5	81.32	534	77.73
	2019 – 2030	3.74	82.28	223.64	46.64



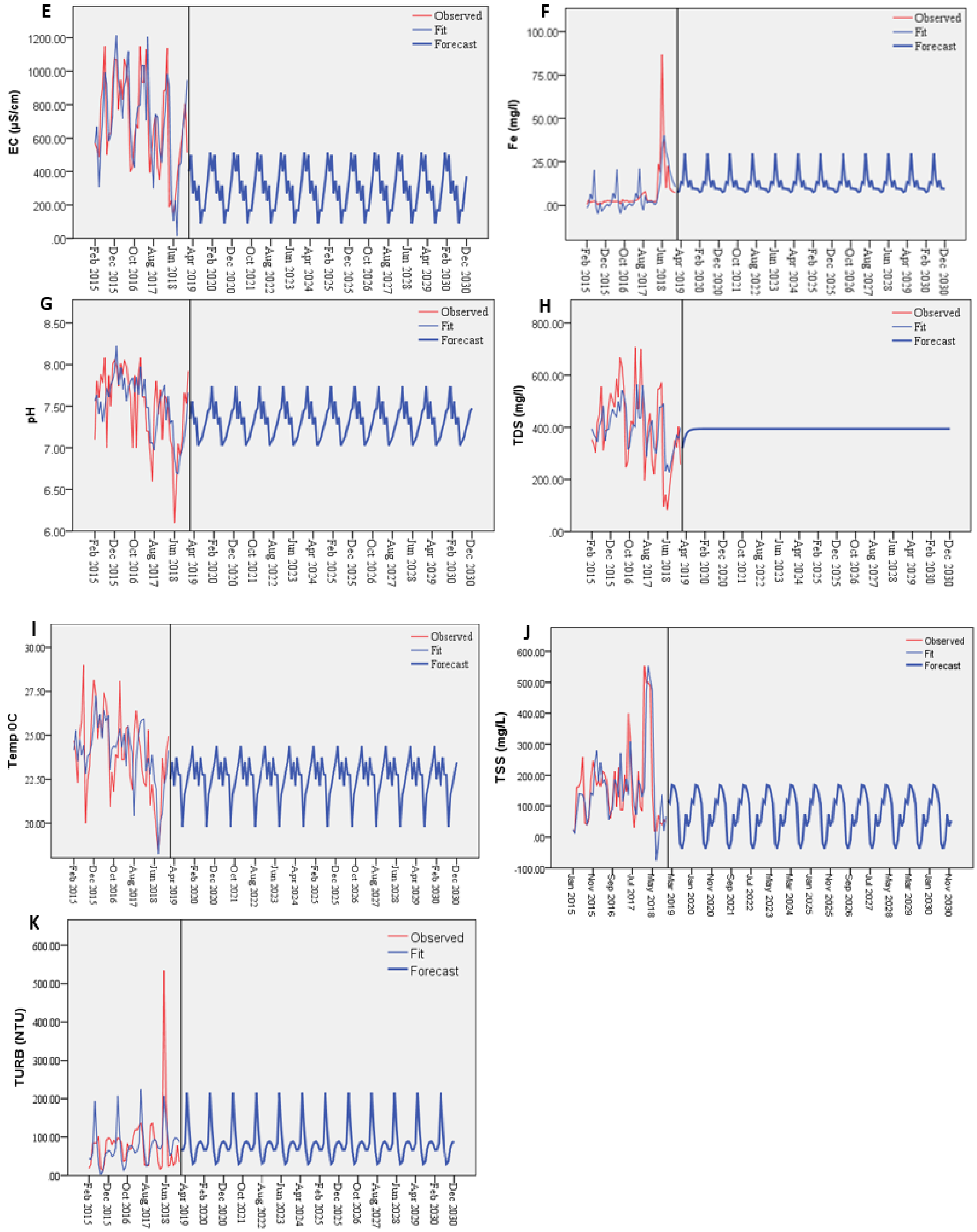
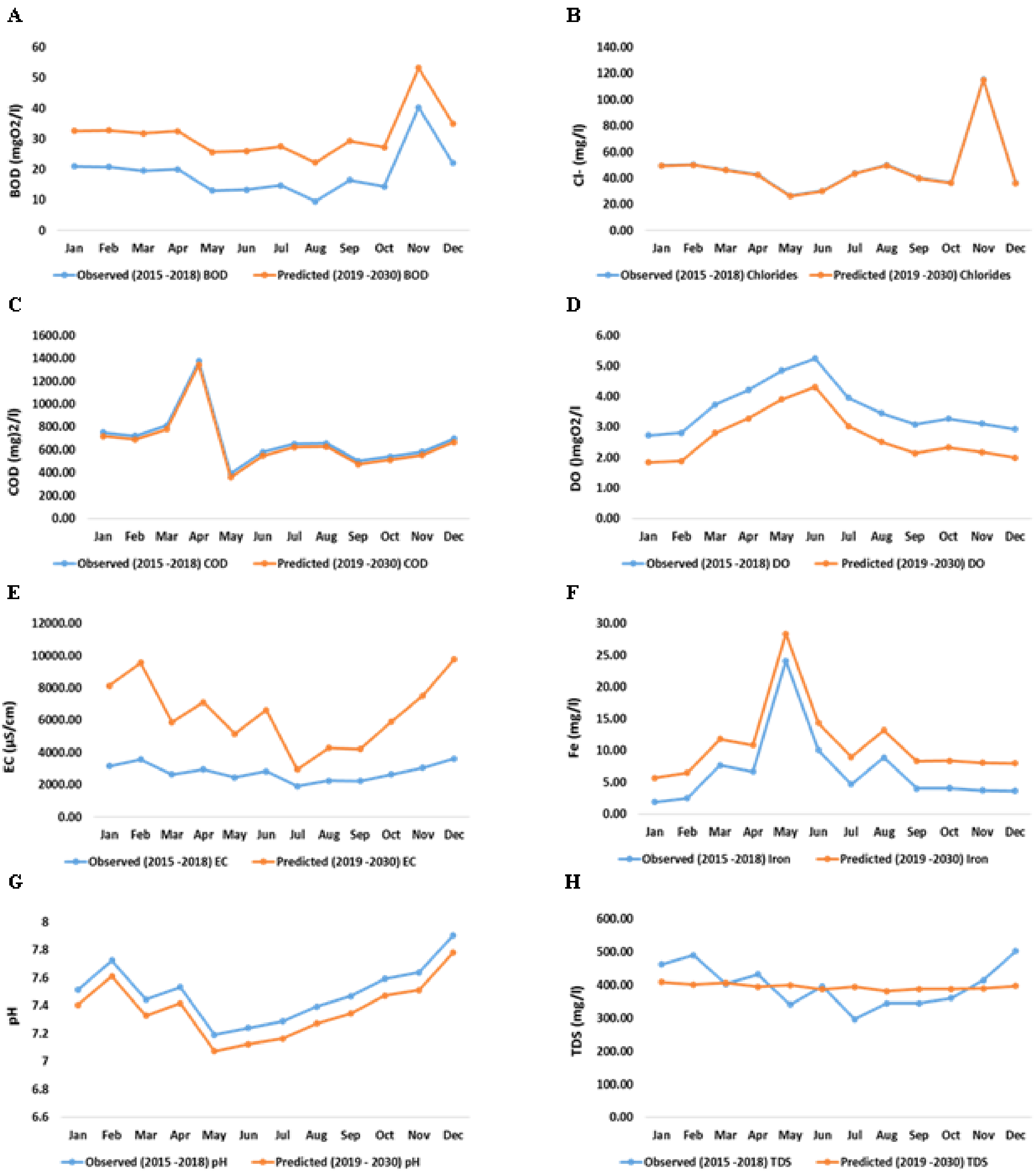


Figure 4 (A - K): Observed and predicted values of the physicochemical parameters in the upper Athi River basin.

Forecasting of the future monthly and annual trends in physicochemical parameters

Even though our model was limited to river discharges, previous models in the upper Athi River revealed that rainfall as well as other socioeconomic factors such as population growth, urban development, forestry and agricultural activities have been used to forecast the physicochemical conditions of this region, and has achieved good performance. In the present study, based on the generated results, the periods between June 2018 and April 2019 exhibited highest BOD values of 160mg/l and 60mg/l respectively for both the observed and predicted BOD curves (Figure 5A). For chlorides, the change was minimal except in April 2019 where the value was 350mg/l (Figure 5B). The future curve presents similar COD concentration for the predicted periods with the exception of June 2018 where the observed value was highest at 3600mg/l (Figure 5C). Based on the generated results, DO concentration fluctuated tremendously between February 2015 and April 2018 with the highest values of 7.8mg/l and 6mg/l for the observed and predicted curves respectively (Figure 5D). Like DO, EC showed fluctuations between February 2015 and April 2018 with the highest values of 1800 (µS/cm) and 1200 (µS/cm) for the observed and predicted curves respectively (Figure 5E). Iron was at peak in June 2018 with values of 86mg/l and 48mg/l for the observed and predicted curves respectively (Figure 5F). pH, TDS and Temp showed great fluctuations between February 2015 to April 2019 but had similar patterns respectively from April 2019 to December 2030 (Figures 5G-5J). Turbidity was highest in June 2018 with value of 540 NTU the observed curves but predicted curves showed slight variations (Figure 5K).



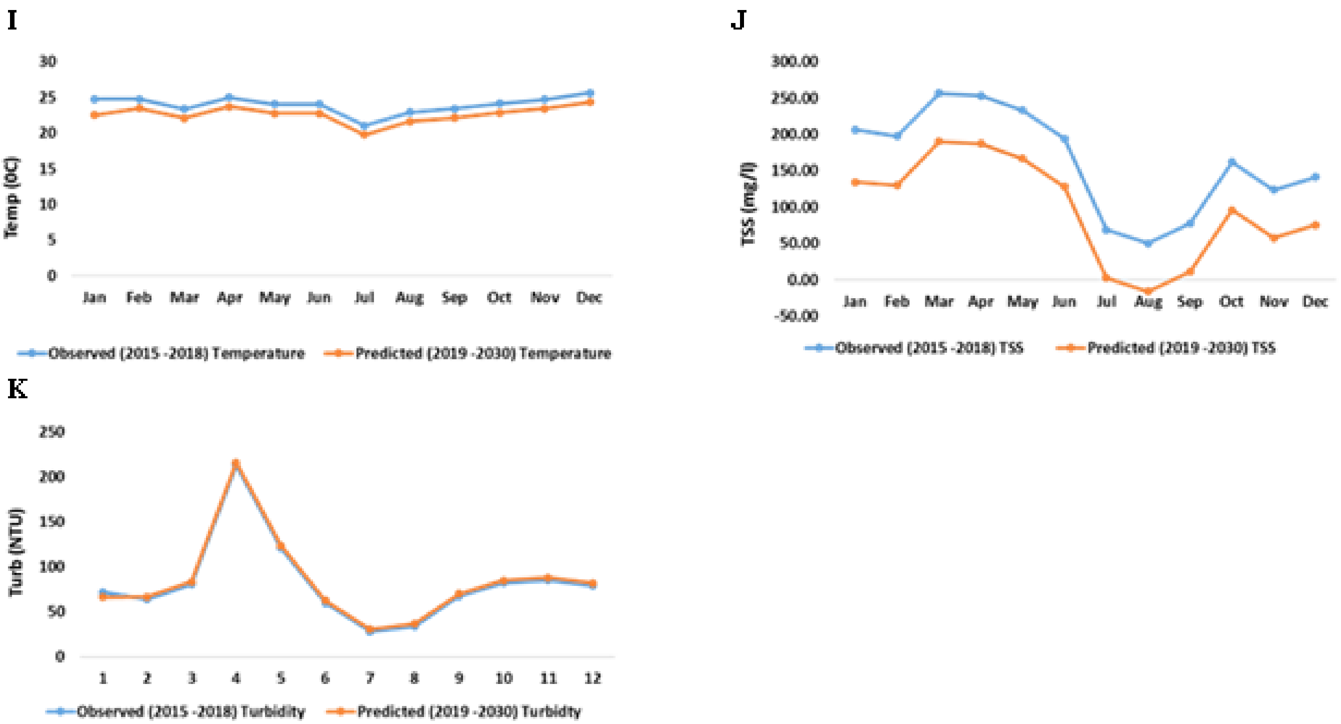


Figure 5 (A - K): Observed and simulated physicochemical parameters values in the upper Athi River basin.

Relationship between discharge and water quality variables

There was a strong direct relationship between discharge and many of the physicochemical parameters (Table 3). The correlation between river discharge values and water quality parameters revealed that there was strong significant ($p<0.05$) relationship between river discharge and turbidity at Nairobi Museum, Thiririka, Ruiru and Kamiti (r= 0.63, 0.96, 0.61 and 0.98 respectively). This is mainly due to the important role played by discharge which is partially a key mechanism via which eroded soil ends up in streams. Similarly, strong significant ($p<0.05$) relationship between river discharge and chlorides was detected at Nairobi Museum, Kiu and Kamiti (r= -0.73, 0.71, and 0.64 respectively). For TSS, strong significant ($p <0.05$) relationship was revealed at 14 Falls, Wamunyu, Thiririka, Ndarugu, Kiu and Kamiti (r= 0.56, 0.94, 0.89, 0.78, 0.53 and 0.91 respectively). Finally, for Fe and Zn all the sites showed significant ($p <0.05$) relationship with the exception of Wamunyu sampling station. Periods of increased discharges were characterized with high TSS while low stream discharges experienced low TSS (Kitheka *et al.*, 2022). Regression results showed that R^2 have very low values that was less than 0.5 (Figure 6) thereby indicating that discharge alone was not sufficient determinant in explaining the physicochemical variables sampled in the present study.

Table 3: Correlation values between discharge and water quality parameters at different sampling sites in upper Athi River basin.

	TURB	Cl	TSS	Fe	Zn
Munyu 14 Falls	0.35	0.36	**0.56**	**0.88**	**0.90**
Wamunyu	-0.43	-0.08	**0.94**	0.45	-0.37
Mbagathi	-0.05	-0.08	-0.12	**0.87**	**0.62**
Nairobi Museum	**0.63**	**-0.73**	-0.28	**0.81**	**0.86**
Thiririka	**0.96**	-0.16	**0.89**	**0.88**	**0.78**
Ndarugu	0.26	-0.34	**0.78**	**0.84**	**0.81**
Ruiru	**0.61**	-0.47	0.26	**0.78**	**0.74**
Kiu	0.30	**0.71**	**0.53**	**0.83**	**0.74**
Kamiti	**0.98**	**0.64**	**0.91**	**0.76**	**0.82**
Ruiruaka	-0.24	0.17	0.13	**0.77**	**0.73**

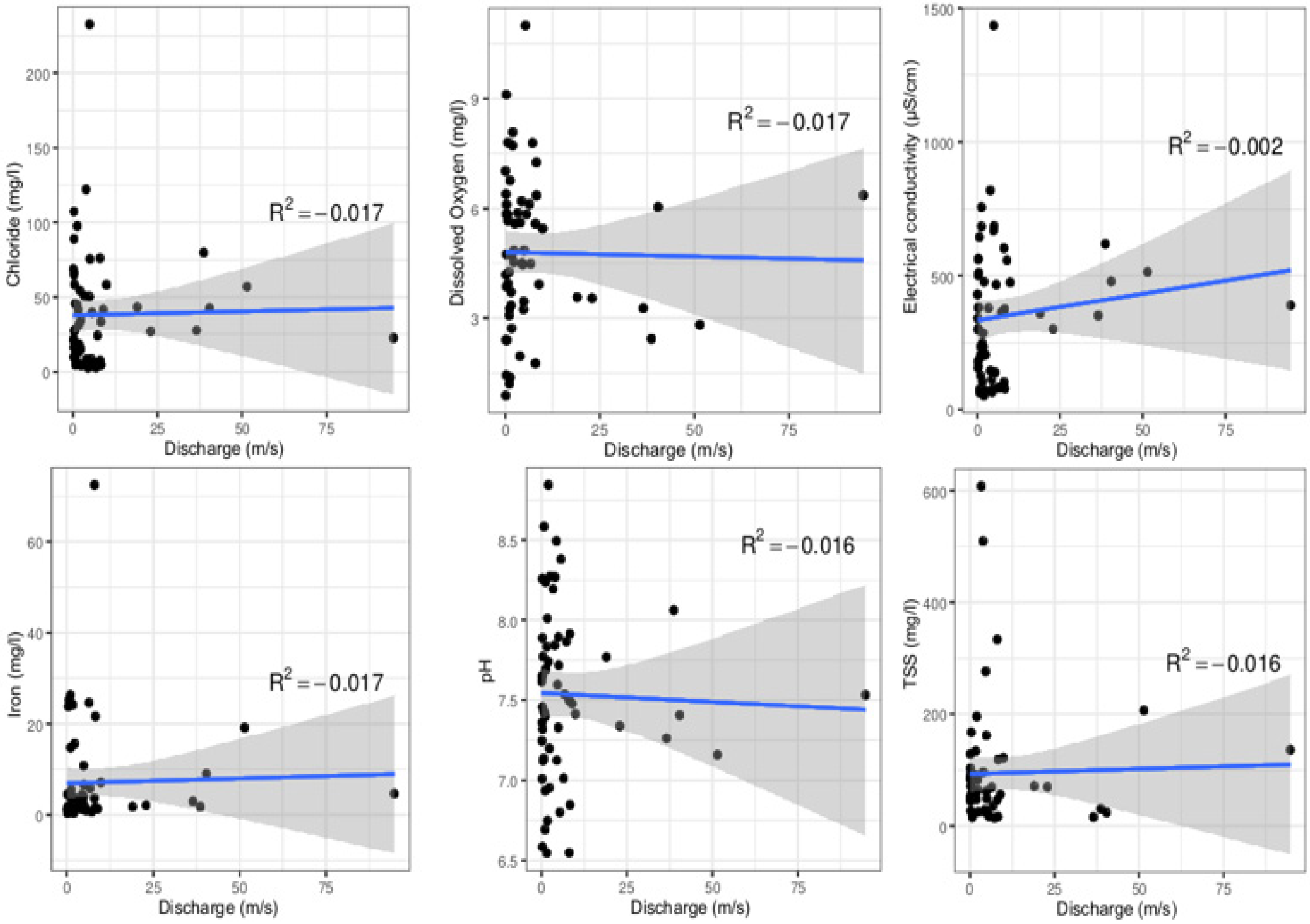


Figure 6: Regression plots of the river discharge and some of the physicochemical parameters in the upper Athi river basin.

DISCUSSION

Comparison of the observed/ measured and simulated physicochemical parameters

The water quality parameters for the calibration and the validation showed that the largest disparity in results observed during the calibration period was with EC, with a standard error of 6.75 and an R^2 value of 0.99. During the validation period, out of all the selected water quality parameters, non-presented a standard error greater than 1.0. The computed values were in the range of 0.01–0.42 and R^2 values in the range of 0.66 – 0.99. Therefore, in this study the validated data fairly agreed very well with simulated data (Table 1), an observation similar to previous study by Abdeveis *et al.* (2020) whose findings showed that QUAL2Kw model calibration results were moderately in agreement with the actual measured data. Additionally, the RMSE between the simulated and observed values in the study by Abdeveis *et al.* (2020) showed minimal disparity in DO, BOD, and pH which is in line with our present study, thus inferring that QUAL2Kw model can be applied in water quality monitoring of upper Athi River with large data, but with caution since further validation of the model output is still required.

Forecasting of future trends in water quality parameters

Forecasting of future trends in water quality parameters is important in decision-making to improve conditions if the forecasts show deteriorating state of certain parameters (Katimon *et al.*, 2018; Kumar, 2017; Taneja *et al.*, 2016). For this study, the water quality parameters considered for forecasting were BOD, Chloride, COD, DO, EC, Iron, pH, TDS, Temperature, TSS and Turbidity because they had available historical data, while TN, TP and Chlorophyll *a* was used to predict the water quality along the Upper Athi river. The findings from the present study revealed that the unprecedented increase in nutrients (TN) levels, BOD, COD, Cl, Fe, and TSS are in agreement with the concept of "urban stream syndrome", postulated by Walsh *et al.* (2005) and emphasized that streams running through urban areas are characterized by increased nutrient levels coupled with degraded physical quality. However, from our findings, the river discharge solely does not strongly explain the concentrations of the physicochemical parameters, hence the need to incorporate other variables like rainfall and socioeconomic factors as done by Kitheka *et al.* (2022) in their previous studies in the same basin. Further, in our present study, COD concentrations increased almost two-fold especially during the wet seasons which is in agreement with previous studies by Mbao *et al.* (2020) who studied Qiantang River Basin, and Ding *et al.* (2017) who worked on Xishuangbanna watershed of the upper Mekong River Basin, China who associated the increased COD to the oxidized cations present in industrial and domestic effluents washed by runoffs from the catchment into the streams. In relation to BOD, the results are in line with previous study by Kithiia (2007) who studied the Nairobi River sub-basins and revealed that the unprecedented population increase within the city piled pressure on the existing drainage and sewage system that occasioned frequent sewer bursts causing increased BOD levels in stream waters especially during the rainy seasons. The increased BOD concentrations are associated to increased level of partially-treated or untreated wastewater from both point and non-point sources (Abdeveis *et al.*, 2020; Arnod *et al.*, 2005; Kithiia, 2007; Radwan *et al.*, 2003; Rosenquist *et al.*, 2013). In the present study, the high mean concentration of TSS for observed and predicted scenarios may infer that there were high erosional activities within the river channel (Chin *et al.*, 2000; Shaw, 2004; Williamson and Crawford, 2011). Similarly, closely related to TSS is turbidity which in the present study was high in the wet season attributed to the heavy rains that eroded the top soil into the river channel (Walsh *et al.*, 2005). Other chemical compounds, specifically Fe^{2+} and Cl^{-} in this study also increased slightly with discharge thus supporting the "urban stream syndrome" which envisages that the causes of water chemistry variations patterns are primarily attributed to events that determines the supply of pollutants (Walsh *et al.*, 2005). Finally, it can be inferred that the model results for the future represent exactly similar trends compared to the observed data.

CONCLUSION

Water quality modeling is a tool that is becoming increasingly useful in obtaining crucial information needed for optimal water quality management. In this present study, the free software QUAL2Kw was used to simulate scenarios of pollutants along Athi River, Kenya, which drains in a heavily industrialized and densely populated area. Scenario-based planning has grown in popularity as a management tool for articulating future water quality models. The Forecasting model was used to predict future water quality scenarios for upper Athi River basin. The model was used to predict the future trends of BOD, Chloride, COD, DO, EC, Iron, pH, TDS, Temperature, TSS and Turbidity in the upper Athi river basin. The DO had a decreasing trend to the future compared to observed, indicating that depletion may occur if no intervention is taken. The pH had slightly higher values for future trends compared to observed values and the TSS observed and simulated data had similar future trends. The predictions for BOD and Iron concentration increased to the future, but there was minimal difference between the observed and predicted chloride levels and posed no threat to the environment. According to this study it can be concluded that the electrical conductivity, BOD and the Fe showed temporal increasing trend for the future prediction results. Therefore, this poses a risk of the Pollutants increasing to unsafe levels if no appropriate management action is taken.

ETHICAL APPROVAL

There was no direct or indirect use of human or animal samples in the course of this research. The research was carried out based on institutional guidelines provided by the Technical University of Kenya for Postgraduate studies.

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