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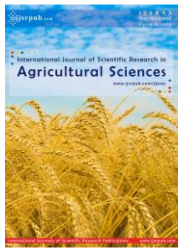

Full Length Research Paper

Receptor Modeling Application on Surface Water Quality and Source Apportionment

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Abstract. There is need for regular monitoring of river water quality to determine specific pollutants in order to aid amelioration schemes. In this study, Principal Component Analysis (PCA) was applied on eighteen water quality parameters; pH, conductivity, dissolved oxygen(DO), turbidity, temperature ,total dissolved solids (TDS), total solids (TS),total hardness (TH), biochemical oxygen demand (BOD), carbon dioxide (CO_2), ammonia (NH_3), nitrate (NO_3^-), chloride (Cl^-), lead (Pb), iron (Fe), chromium (Cr), copper (Cu) and manganese (Mn) to identify major sources of water pollution of river Asa. The generated Principal Components (PCs) were used as independent variables and water quality index (WQI) as dependent variable to predict the contribution of each of the sources using multiple linear regression model (MLR). The PCs results showed that the sources of pollution are storm water runoff, industrial effluent, erosion and municipal waste, while MLR identified storm water runoff (0.786) and industrial effluent (0.241) as the respective major contributors of pollution. The study showed that PC-MLR model gives good prediction (R^2=0.8) for water quality index.

Keywords: multiple linear regression, principal component analysis, river Asa, water quality

1. INTRODUCTION

Progressive technological improvement in recent times has helped in booming the industrial and many other sectors. The positive effect of this is evident in speedy economic development in many countries of the world. This however, is not without any challenge, as it is accompanied by environmental (basically water and air) pollution (Kamaruddin et al., 2013). Urbanization for instance is bringing about a rapid replacement of natural surfaces with artificial ones with its resultant effect on runoff generation.

Surface water, a vital component of the environment is a major recipient of the pollutants. Its high susceptibility to pollution is due to easy accessibility of natural and anthropogenic activities from its surrounding to it (Nasir et al., 2012). Good quality of river water is highly essential for man's need on earth as the state of water, food and ultimately the health of man largely depends on it. A number of natural and anthropogenic factors affect the quality of water, out of which storm water runoff, industrial effluent, municipal and agricultural wastes seem to be the major polluting sources (Akinwunmi and Eletta, 2013, Omole and Longe, 2008)

The constituent of these wastes varies with their sources. While the Industrial discharges are mostly rich in heavy metals, agricultural wastes majorly contain organic matters which are compounds of nitrogen and phosphorus from fertilizers, pesticides, salts, abattoir wastes and animal excreta (Omole and Longe, 2008). The entry of any or all of these wastes into surface water alters the chemistry of the water, changing (increase or decrease) the level of parameters above or below the established standards (Ewa et al., 2013). Due to these variations in the chemistry of surface waters, there is need for regular assessment of water quality for evaluating the nature and degree of corrective measure needed (Jiwen et al., 2013). This will allow for maintenance or restoration to recommended level.

In water quality assessment, identification of sources of pollution and the contribution of each of the sources used to be a major challenge in explaining water quality deviation from allowable limit until recent time (Adamu and Ado, 2012). Ewa et al.

(2013), Jiwen et al. (2013) and Adamu and Ado (2012) listed a number of researchers who employed Principal Component Analysis (PCA) to identify pollution sources and Multiple Linear Regressions (MLR) in estimating the contribution of each of the sources. Among the researchers mentioned is Hai et al. (2009) that claimed with the use of PCA that pollution of Taihu lake region in China was due to anthropogenic activities namely; urban residential subsistence, livestock farming and farmlands run-off. Also Koklu et al. (2010) identified important parameters that contributed to the water quality variation in Melen River system, Turkey with the use of multiple regressions.

The water quality index of river Asa in Ilorin is ranked as poor (Ahaneku and Animashaun, 2013). This study attempts to verify sources of pollution leading to the poor ranking of river Asa using principal component analysis; and to evaluate the contribution of each of the sources towards water quality variation using multiple linear regression models.

2. Materials and Methods

2.1. Study Area

River Asa is the longest river that flows across Ilorin city. The river flows in south-north direction and covers an area of about 104 km^2 (8^0 36'- 8^0 24' N; 4^0 36' – 4^0 l0'E) dividing Ilorin city into eastern and the western part (Ahaneku and Animashaun, 2013). It is a major river of economic, agricultural, and environmental significance in the city. The river has a shallow depth of between less than 10 m and 14m from the surface (Adekola and Eletta, 2007; Adewoye 2013). It is dammed 2km south of the city to supply water for domestic and industrial usage. The river water is used by the people of Ilorin and its environs for different activities depending on its point of contact. The river runs through residential and commercial areas, serving as a recipient of domestic waste (sewage), agricultural waste runoff and industrial effluents from industries such as Soap and Detergent Industries Limited, 7up Bottling Company, TUYIL Pharmaceuticals Nigeria Limited, Dangote Flour Mill, Nigeria Bottling Company (Coca-Cola) Ilorin Plant among other industries located along its bank.

2.2 Sampling and Analytical Techniques

Water sampling was carried out in both wet and dry seasons of the year 2012 at four different locations (Asa Dam Bridge, Unity Bridge, Emir's road Bridge and Amilegbe Bridge) along river Asa. A total of 576 observations were recorded. The sampling locations (Figure 1) were planned to cover some distances that will give a reflection of different activities carried out on the river. The samples were collected using plastic bottles rinsed with trioxonitrate (V) acid and distilled water to avoid unpredicted change in the characteristic of the water samples. The bottles were marked and labelled in reference to the sampling points. Each of the samples was analyzed for some physicochemical parameters namely: pH, conductivity, dissolved oxygen (DO), turbidity, temperature, total dissolved solids (TDS), total solids (TS),total hardness (TH) biochemical oxygen demand (BOD), carbon dioxide (CO_2), nitrogen in the form of ammonia ($NH_{3)}$ and nitrates (NO_3^-) , chloride (Cl^-) and five heavy metals (Pb, Fe, Cr, Cu, Mn).

The pH, conductivity, dissolved oxygen; turbidity and temperature were measured using pH meter, conductivity meter, dissolved oxygen meter, turbidity meter and thermometer, respectively. Carbon dioxide, Chloride, Total dissolved solid, Total solid, Total hardness, Biochemical oxygen demand, Nitrate and Ammonia were determined using standard methods recommended by the American Public Health Association (APHA, 1995), and the heavy metals were determined using atomic absorption spectrophotometer (AAS). Ten of the water parameters (DO, pH, temperature, turbidity, TDS, NH_3, $NO_{3,}$ Pb, Fe, and Cr) measured were used for the determination of water quality index of the river, while the eighteen parameters were employed for the source apportionment of the river using PCA, and the new variables (retained PCs) obtained were used for the modeling.

2.3 Data Treatment

Before the application of principal component analysis on the data, Keiser-Meyer-Olkin (KMO) measure of sampling adequacy (usually called MSA) and Bartlett's test of sphericity were verified. This was to examine the suitability of the data for principal component analysis (Jiwen et al., 2013). KMO is a measure of sampling adequacy which indicates the strength of connection between variables. High values like 0.5 and above are desirable and values below it are considered undesirable (Shrestha and Kazama, 2007). Bartlett's test of sphericity checks whether or not correlation matrix is an identity matrix. If the matrix is an identity one, it implies that variables are unrelated and thus, PCA cannot be performed. The MSA can be performed for each variable through determination of anti-image matrices and for all the variables through KMO. Statistical computation of PCA and MLR were carried out using SPSS for window (version 20).

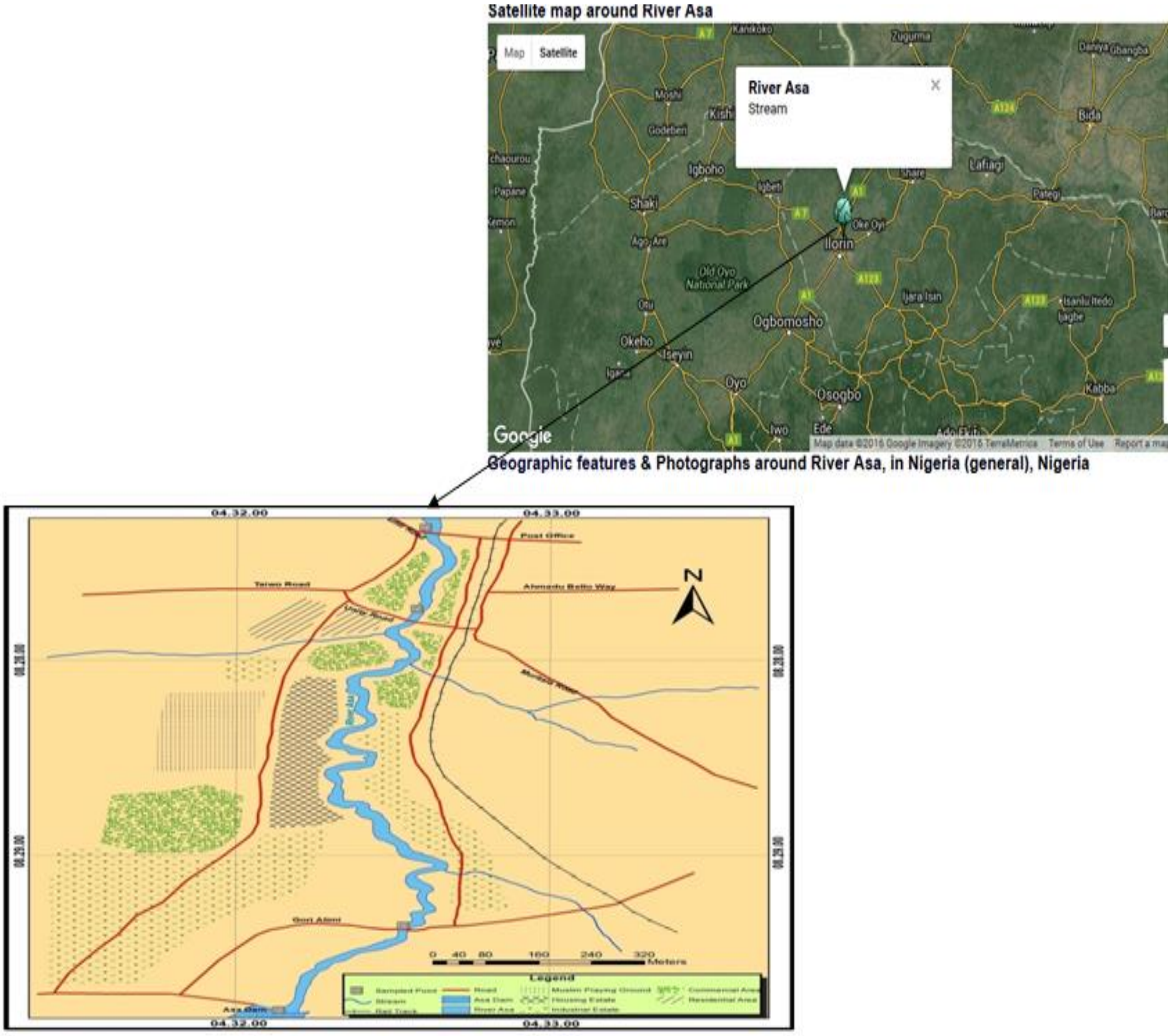


Fig. 1: Sampling locations

2.4. Principal Component Analysis

Principal Component Analysis (PCA) is a traditional multivariate statistical method. It is one of the most powerful techniques commonly used in explaining the variance of a large set of inter-correlated variables and reducing them into smaller set of independent (uncorrelated) artificial variables called Principal Components(PCs) (Shrestha and Kazama 2007). PC is a linear combination of the original variables, which provides information on the most meaningful parameters (Jiwen et al., 2013). These parameters are considered most meaningful because they account for most of the variance in the observed variables. PCA summarises a whole data set with a smaller number of PCs with a minimum loss of original information. The magnitude of the variance capture by the PCs decrease with the number of axis, whereas the first PC captures the greatest variance, the second greatest variance is on the second PC and so on (Ul-Saufie et al., 2011).

PCA was performed on the measured water quality data to extract the most significant parameters. The extracted PCs were further subjected to rotation (using varimax) to produce factors (varimax factor), thus reducing the dimensionality of the data and identifying most significant new variables for easy interpretation of data (Ul-Saufie et al., 2011). Varimax factor (VF) coefficient with a correlation greater than 0.75, and between 0.75-0.50 and 0.50-0.30 are considered as strong, moderate and weak factor loadings, respectively (Shrestha and Kazama, 2007). Loadings refer to the (relative) contribution of a variable to a principal score.

Table 1: Statistical summary of wet season surface water quality parameters from river Asa, Ilorin

Station	Statistical tool	DO mg/l	pH mg/l	Temp oC	Turb NTU	NH_3 mg/l	NO_3 mg/l	TDS mg/l	Pb mg/l	Fe mg/l	Cr mg/l	Cu mg/l	TS mg/l	Cl mg/l	Mn mg/l	CO2 mg/l	TH mg/l	Cond mg/l	BOD mg/l
Asa	Mean	6.25	7.03	27.02	8.83	0.03	2.70	249.00	0.02	0.53	0.06	0.50	315.50	6.00	0.32	7.50	48.00	86.14	3.95
	Maximum	7.60	7.20	27.40	10.30	0.04	2.74	258.00	0.03	0.60	0.07	0.60	386.00	6.50	0.35	8.50	50.00	89.18	5.20
	Minimum	4.80	6.90	26.59	7.50	0.02	2.66	244.00	0.00	0.40	0.05	0.40	284.00	5.50	0.30	6.50	46.00	83.76	2.80
	SD	1.36	0.15	0.35	1.16	0.01	0.03	6.22	0.01	0.10	0.01	0.08	47.37	0.41	0.02	0.16	1.83	2.29	1.14
Unity	Mean	5.28	7.98	28.02	13.58	0.04	3.29	260.50	0.06	1.38	0.08	0.70	318.80	9.75	0.42	2.00	52.00	96.23	3.20
	Maximum	6.80	8.10	28.20	15.80	0.05	3.35	268.00	0.09	1.50	0.09	0.90	328.00	10.50	0.50	2.50	56.00	101.40	4.80
	Minimum	4.10	7.90	27.94	10.50	0.04	3.25	254.00	0.04	1.20	0.06	0.50	306.00	9.00	0.35	1.50	48.00	89.08	2.30
	SD	1.15	0.10	0.12	2.26	0.01	0.05	5.97	0.02	0.13	0.01	0.16	9.29	0.65	0.06	0.29	3.65	5.21	1.12
Emir	Mean	5.53	7.40	27.71	15.08	0.05	3.81	267.00	0.06	1.10	0.06	0.40	333.80	8.88	0.31	4.50	48.00	90.85	3.88
	Maximum	6.80	7.60	27.92	19.50	0.06	3.87	286.00	0.08	1.40	0.07	0.50	348.00	10.00	0.32	5.00	50.00	93.57	5.00
	Minimum	4.20	7.20	27.40	12.00	0.05	3.74	256.00	0.03	0.80	0.06	0.30	324.00	7.50	0.30	4.00	46.00	87.26	2.60
	SD	1.19	0.18	0.25	3.36	0.00	0.06	13.32	0.02	0.26	0.01	0.08	10.53	1.11	0.01	0.18	1.63	2.76	1.20
Amil	Mean	5.08	7.50	27.94	16.13	0.09	4.18	273.8	0.06	1.08	0.06	0.40	344.50	11.10	0.33	6.50	48.00	89.63	4.03
	Maximum	6.20	7.80	28.10	20.50	0.12	4.40	290.00	0.09	1.40	0.07	0.50	355.00	12.50	0.40	7.50	50.00	92.24	5.00
	Minimum	4.20	7.30	27.80	13.50	0.07	4.00	263.00	0.03	0.50	0.06	0.30	336.00	8.50	0.25	5.00	46.00	84.46	3.20
	SD	1.03	0.22	0.12	3.20	0.02	0.17	11.50	0.03	0.28	0.01	0.08	8.35	1.78	0.06	0.22	1.63	2.42	0.87

Table 2: Statistical summary of dry season surface water quality parameters from river Asa, Ilorin

Station	Statistical tool	DO mg/l	pH	Temp oC	Turb NTU	NH_3 mg/l	NO3 mg/l	TDS mg/l	Pb mg/l	Fe mg/l	Cr mg/l	Cu mg/l	TS mg/l	Cl mg/l	Mn mg/l	CO2 mg/l	TH mg/l	Cond mg/l	BOD mg/l
Asa	Mean	4.03	7.25	27.80	9.38	0.05	3.80	241.00	0.01	0.63	0.06	0.40	288.00	7.23	0.31	9.50	52.00	92.88	3.18
	Maximum	5.00	7.90	28.26	10.50	0.05	4.20	282.00	0.02	0.70	0.50	0.50	328.00	8.20	0.40	10.00	54.00	98.00	4.20
	Minimum	3.20	6.80	26.94	7.00	0.05	3.50	206.00	0.00	0.04	0.30	0.30	256.00	6.00	0.25	9.00	50.00	87.26	2.30
	SD	0.91	0.48	0.59	1.65	0.00	0.29	33.25	0.01	0.01	0.01	0.01	31.88	1.01	0.06	0.41	1.63	4.45	0.97
Unity	Mean	3.58	8.25	28.61	12.48	0.06	5.08	283.00	0.08	1.73	0.08	0.80	344.00	13.00	0.44	3.00	56.00	101.00	3.70
	Maximum	4.40	8.50	28.96	17.90	0.06	6.10	344.00	0.16	1.90	0.10	0.90	422.00	16.00	0.50	4.00	60.00	110.00	4.20
	Minimum	3.00	80.00	27.80	9.00	0.05	4.20	248.00	0.03	1.50	0.06	0.70	292.00	9.00	0.35	2.50	52.00	92.02	3.20
	SD	0.59	0.21	0.55	4.14	0.01	0.78	44.47	0.06	0.17	0.02	0.01	55.88	2.94	0.07	0.71	3.65	8.40	0.42
Emir	Mean	3.50	7.60	28.46	16.38	0.07	5.58	314.50	0.06	1.18	0.06	0.60	382.50	10.10	0.35	5.50	52.00	94.50	3.10
	Maximum	4.20	7.90	28.94	23.50	0.08	6.20	388.00	0.11	1.80	0.07	0.70	468.00	12.00	0.40	6.00	54.00	98.00	3.60
	Minimum	2.90	7.40	27.90	11.00	0.06	4.80	280.00	0.03	0.80	0.05	0.40	336.00	6.00	0.30	4.50	50.00	91.47	2.80
	SD	0.61	0.22	0.54	5.59	0.01	0.64	50.05	0.04	0.45	0.01	0.14	59.36	2.84	0.04	0.71	1.63	3.18	0.36
Amil	Mean	3.48	7.43	28.57	17.83	0.13	6.35	334.50	0.07	1.50	0.06	0.60	403.50	11.10	0.35	7.00	48.00	92.65	3.48
	Maximum	4.00	7.90	29.10	26.80	0.20	7.60	418.00	0.13	1.90	0.07	0.70	490.00	14.00	0.40	8.00	50.00	96.00	3.80
	Minimum	2.90	7.10	28.10	12.50	0.06	5.20	294.00	0.03	0.80	0.06	0.50	352.00	16.00	0.31	6.00	46.00	89.58	3.20
	SD	0.48	0.36	0.42	6.67	0.07	1.23	56.44	0.04	0.50	0.01	0.01	60.00	3.52	0.04	0.91	1.63	2.66	0.25

2.5. Determination of Water Quality Index

Determination of Water Quality Index of the river was done using Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) (Ahaneku and Animashaun, 2013). The Index is based on the combination of three measures of variance from selected water quality standard (scope, frequency and amplitude). The Index compares the compliance of the observed data to a water quality standard to give a score ranging from 0, indicating worst quality to 100 signifying the best quality. After determining CCME WQI, the water quality was ranked as poor (Ahaneku and Animashaun, 2013).

2.6. Multiple Linear Regressions

Multiple linear regression is a statistical tool for describing a quantitative relationship between several predictors (independent variables) and a dependent variable to test specific hypotheses based on a scientific theory or prior research (Ul-Saufie et al., 2011). It is commonly performed with principal component scores for source apportionment of air pollution (Nasir et al.., 2012). In recent time, it is gaining popularity in apportioning source of water pollution (Nasir et al., 2012).

The preference given to principal component scores in place of the raw data (water parameters) for the modeling was due to its elimination of collinearity problems and prediction improvement (Ul-Saufie et al., 2011). MLR was used to examine the relationship between the source apportionment generated by PCA and their correlation to WQI values. WQI values were used as dependent variable, while the VFs were used as independent variables.

3. RESULTS AND DISCUSSIONS

3.1. Principal Component Scores and Source Apportioning

In this study, the anti-image values of MSA for each of the variables, the KMO for the overall variables and Bartlett's test for the overall MSA are good values, indicating validity of factor analysis. The value of KMO test was 0.743 and Bartlett's test of sphericity was at significance level (less than 0.05) meaning that there are significant relationships among variables. This signifies the appropriateness of principal component analysis for making significant reduction in the data dimensionality. The statistical summaries of wet and dry season's surface water quality parameters from river Asa used for PCA are presented in Tables 1 and 2, respectively.

Four varimax factors (VFs) with total variance of 78.22 % were produced after varimax rotation based on Kaiser Criterion. In Kaiser Criterion, only components with eigenvalues greater than one are retained and SPSS follows this rule (Nasir et. al, 2012). Each of the retained components contains a subset of the original variables with different loading. The component loadings greater than 0.6 was taken into consideration in the interpretation of the water quality data as opined by Nazire et al. (1999). The loading of each of the variables, their communalities, and the eigenvalues with their corresponding percentage of variance are presented in Table 3. Communalities give an index of the efficiency of the reduced set of components and degree of contribution of each variable in the retained four components. The communalities showed that the variance of each of the variables has been described to an acceptable level (Nazire et al, 1999). Though, each of the water quality parameter relates with and influences other parameters in complex ways, their ways of clustering points to a common origin.

VF1 has an eigenvalue of 8.066 which correspond to 44.81% of the total variance. It has strong positive loadings on TS, NO_3, Turbidity, NH_3, TDS and moderate positive loading on Pb, Fe, Temperature and Cl^-. It can be inferred from the loadings on this component that the river water quality is being compromised by the effect of storm water runoff. The probable source of the heavy metals (such as Pb) in runoff could be from automobile emission which is bound to dust, the iron-rich soil of the city and other particles on the road surfaces that dissolve or move in runoff water thus making storm water runoff in Ilorin a significant source of heavy metals as reported by Adekola et al. (2001) and Adekola and Eletta (2007).

Two nitrogenous compounds (NH_3-N and NO_3-N) load on this component. The common source of nitrogen includes soil, decaying plants and animals, fertilizers, untreated sewage, as well as domestic waste (Kitt, 2000). The loading of ammoniacal nitrogen on this component showed that the probable presence of bacterial, sewage, and animal waste pollution is due to decomposition of nitrogenous organic matters which were washed into the river. Our result is in conformity with the report of New Jersey (2002). High turbidity of the river due to suspended particles and dissolved solids carried by storm water runoff increases the water temperatures (Adewoye, 2013). The VF1 also has chloride which is one of the ions contained in total dissolved solids (TDS) and its probable source is animal waste and fertilizer runoff. Our results are in agreement with those of Adewoye (2013) who found that nitrate and chloride are washed into the river during the rainy season. The total sums of all the variables that load on VF1 seem to have their common origin from non- point source pollution through storm water runoff.

VF2 with an eigenvalue of 3.301 explains 18.338% of the total variance. This component with strong positive loading on Cr, moderate positive loading on Mn, Cu, and pH and strong negative loading on CO_2 may indicate industrial effluent discharge. The source of Cr and Cu in river Asa could be attributed to pharmaceutical effluent in accord with the findings of Olaitan et al. (2013). Cr could also be from bottling company effluent or from tannery or detergent industries effluent (Peoples' Science Institute, 2006; Adekola and Eletta 2007). The high pH value of river Asa at some locations during the dry season as observed in the raw data is also linked to the point source discharge of poorly or non-treated effluent from the soap and detergent industry. Similarly, the presence of Mn and Cu in the river points to the effluent from the soap and detergent industries sited near river Asa. The results are in agreement with the findings of earlier researchers (Justice et al., 2011 and Adewoye, 2013).

Table 3: Rotated component matrix

Parameters	VF1	VF2	VF3	VF4	Communalities
TS	**0.881**	-0.014	0.130	0.054	0.796
NO_3	**0.873**	-0.046	0.289	0.083	0.854
Turbidity	**0.870**	0.085	-0.007	0.003	0.765
NH_3	**0.861**	-0.128	-0.119	0.053	0.774
DS	**0.810**	0.036	-0.020	0.186	0.693
Pb	**0.719**	0.369	0.334	0.040	0.767
Temperature	**0.702**	0.229	0.504	0.225	0.850
Fe	**0.674**	0.589	0.293	0.109	0.898
Cl	**0.632**	0.451	0.315	0.012	0.703
CO_2	0.031	**-0.826**	-0.250	0.147	0.767
Cr	-0.090	**0.803**	-0.141	0.401	0.833
Mn	0.021	**0.699**	0.212	-0.170	0.563
pH	0.281	**0.648**	0.523	0.113	0.785
Cu	0.156	**0.633**	0.517	0.121	0.591
TH	-0.044	0.161	**0.896**	0.204	0.872
Conductivity	0.294	0.397	**0.724**	0.095	0.777
BOD	-0.064	-0.002	-0.149	**-0.935**	0.901
DO	-0.465	0.028	-0.397	**-0.720**	0.893
Eigen Value	8.066	3.301	1.688	1.025	
Variance (%)	44.812	18.338	9.380	5.692	
Cumulative (%)	44.812	63.150	72.530	78.222	

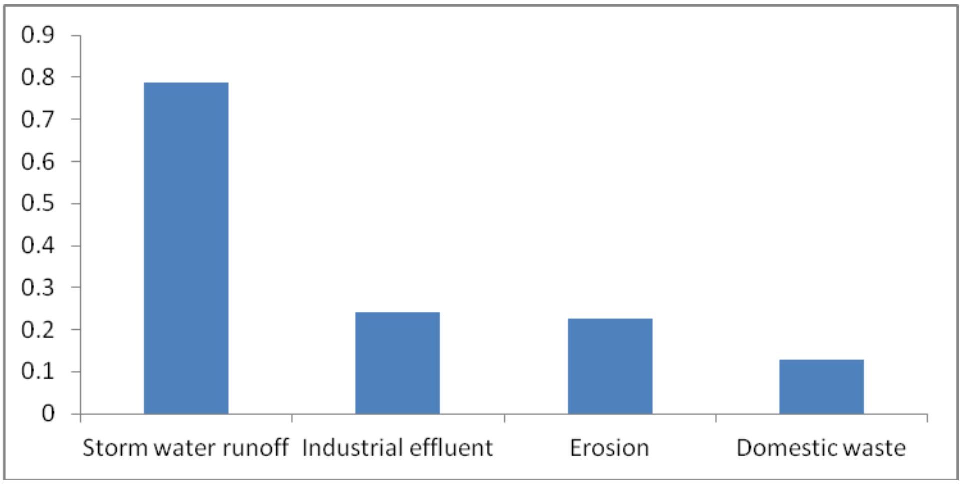
Table 4: Analysis of variance for the prediction of source of pollution of river Asa

Model	Sum of Square	Df	Mean square	F	Sig
Regression	290.434	4	72.608	13.414	0.000*
Residual	70.366	13	5.413		
Total	360.800				

*- significant by F test at 5% probability

A strong negative loading of CO_2 shows an inverse correlation between CO_2 and other parameters that load on the component. This indicates decrease in CO_2 as other parameters on the component increase. Its loading on this component showed that the probable source is industrial. The presence of CO_2 may be due to the effluent discharges of carbonate ion from factories (Pharmaceutical, bottling companies) which use carbonated substances in their production, or from fossil fuels burning from the industries which is absorbed by the river (Nagendra and Ram, 2011; William and Wei-Jun, 2012). VF3 has an eigenvalue of 1.688 which explains 9.380% of the total variance. This component with loadings on conductance and total hardness can be referred to as the salt or mineral component (Naima et al., 2013). Total hardness and conductivity of the water are due to the presence of calcium carbonate, sulphate, chloride and nitrate of calcium and magnesium. The principal natural sources of hardness in water are dissolved polyvalent metallic ions from sedimentary rocks, seepage and runoff from soils. Calcium and magnesium, the two principal ions, are present in many sedimentary rocks, the common rock in Ilorin city (Ibrahim et al., 2012). Although magnesium is used in many industrial processes, it contributes relatively little to the total magnesium in surface waters (Chapman and Kimstach, 1996). The geology surrounding the water body is largely the source of hardness. The dissolution of limestone and gypsum soils from sedimentary rocks suggests soil erosion process.

VF4 has an eigenvalue of 1.025 with a corresponding total variance of 5.692%. This last component with loadings on BOD and DO indicate the anthropogenic input, usually organic pollution. The presence of high levels of dissolved organic matter could be linked to waste disposal activities (domestic or municipal waste). Wastes that are rich in organic matter and nutrients can reduce the concentrations of DO as a result of increased microbial activity taking place during the degradation of the organic matter (Chapman and Kimstach, 1996). The DO value of a river can signify the extent of pollution by organic matter and the level of self-purification of the water.



Dependent variable: Water quality index, p-value <0.001

Fig. 2: Estimation of coefficients of the multiple linear regression models

3.2. Prediction of main source of pollution of river Asa using PC-MLR Model

Storm water runoff, Industrial discharge, Erosion and Municipal waste were used to assess the best predictor of water quality index of river Asa. To achieve this, standard multiple linear regression model was employed. Before the interpretation of the models, usual assumptions (such as linearity or model fitness, normality, and multicolinearity) of regression were checked and the models were found to be in conformity with the assumptions. Table 4 shows the summary of analysis of variance (ANOVA) for the prediction of source of pollution of river Asa with a highly significant p-value ($p < 0.001$) indicating linear relationship between the predictors of the models. The model summary (Table 5) showed that 81% of the variance of water quality index was explained by the four PCs (R^2 =0 .805, Adjusted R^2 = 0.745). Water quality index was used as dependent variable, while the four PC values were used as independent variables. Water quality index was principally predicted by storm water runoff which has the strongest weight (0.786) in the model, followed by industrial discharge (0.241) and erosion (0.226). The least contributor is municipal waste (0.129) (Figure 2).

Table 5: PC-MLR Model summary

R	R^2	Adjusted R	Std. Error of the Estimate
0.897	0.805	0.745	2.326

Predictors: (Constant), Municipal waste, Industrial effluent, Erosion, Storm water runoff

4. CONCLUSIONS

The sources of water pollution leading to the poor ranking of river Asa were verified using PCA. The contribution of each of the sources towards water quality variation was evaluated with MLR model. The sources of pollution of river Asa are diverse in nature. Storm water runoff was identified as the major source of pollution of river Asa. Next to it is anthropogenic activities from industrial effluent discharges. The highest weight (R^2 = 0.786) of storm water runoff could be due to washing and flushing of different types of waste (liquid, slurry and solid) from diverse non- point sources (urban, agricultural and industrial area) into the river. The nearness of a number of industries which discharge effluents into the river could be the reason for the second highest weight of “effluent discharge” as a source of pollution. The significant weight of domestic (or municipal) waste as a source of pollution could be as a result of waste disposal along the bank of the river. The results of the study showed that PC-MLR model gives good accuracy for WQI forecasting (R^2= 0.8) and the model indicates that 81% variability of WQI was explained by the four independent variables used in the model.

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