https://doi.org/10.33271/nvngu/2024-1/122

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MODELING PH CHANGES AND ELECTRICAL CONDUCTIVITY IN SURFACE WATER AS A RESULT OF MINING ACTIVITIES

Purpose. To develop comprehensive models for predicting the pH and electrical conductivity of surface water in Maiganga coal mine and environs affected by mining activities.

Methodology. The research utilizes a combination of in-situ measurement, laboratory analysis, modeling technique using Ansys Workbench and Linear Regression for predicting the content of pollutants. In-situ measurement/data collection in the upstream and downstream were carried out to evaluate the potential impact of mining activities on surface and ground water quality. Electrical conductivity and pH were measured on the samples that were collected using Oakton 5/6 pH meter and TDS/EC meter.

Findings. According to the results, the regression statistics model of pH and electrical conductivity (EC) shows that the predicted values have a pH range of 4.7–7.05 and a mean pH value of 5.5. In contrast, while the EC ranges from 454.52 to 2,720.68 μs/cm (EC) with a mean value of 905 μs/cm of the downstream flow which is completely dependent on the mine inlet (pH-in and EC-in). The findings show a direct correlation between surface water pH, electrical conductivity, and mining activities in the Maiganga coal mine area and their detrimental effects on the ecosystem and water quality.

Originality. The results were obtained directly from the mine site during field visit and can be compared to data from active coal mine sites.

Practical value. The detrimental effect of the results of mining activities can be controlled if monitoring sensors are introduced at mines' effluent outlet to alert the mine management of possible danger in real time.

Keywords: *Maiganga coal mine, pH, electrical conductivity, predictive modeling, surface water, environmental monitoring*

Introduction. Toxic effluent released by mining operations around the world has negatively impacted the surrounding area's surface and groundwater quality, as well as the environment surrounding the operation itself. The pH and electrical conductivity of surface water are crucial parameters that provide valuable information about water quality and the potential effects of mining activities [1]. Monitoring and modeling these parameters can aid in understanding the environmental impact of mining operations and facilitate effective water management strategies [2]. Coal mining involves various processes, such as excavation, transportation, and waste disposal, which can introduce pollutants into nearby surface water bodies. These pollutants can alter the chemical composition of water, affecting its pH and electrical conductivity [3]. Deviations from the natural pH and electrical conductivity levels can harm aquatic ecosystems, posing risks to both aquatic ecosystems and human populations that rely on these water sources [4].

pH represents the acidity or alkalinity of water and is measured on a logarithmic scale ranging from 0 to 14, with 7 being considered neutral. Changes in pH can influence the solubility, mobility, and toxicity of chemicals in water [5]. Electrical conductivity, on the other hand, measures the ability of water to conduct an electrical current and is related to the presence of dissolved ions, including salts and other conductive substances. Elevated electrical conductivity levels can indicate the presence of pollutants or dissolved solids in water [6].

Adeyemo, et al. [7] developed a model for predicting the electrical conductivity of surface water in mining areas using input parameters such as pH, temperature, and total dissolved solids. The results showed that the model had a high accuracy in predicting surface water pollution's pH and electrical conductivity from gold mining activities. The model used input parameters such as total suspended solids, pH, and electrical conductivity to predict surface water's pH and electrical conductivity. The results showed that the model had a high accuracy in predicting the pH and electrical conductivity of surface water pollution from gold mining activities.

To effectively manage and mitigate the impact of mining activities on surface water quality, it is crucial to develop models that can accurately predict the pH and electrical conductivity levels based on various influencing factors [8]. These factors may include the proximity of mining sites, the nature and extent of mining operations, the presence of specific pollutants, and the area's natural hydrological and geological characteristics [9].

By modeling surface water's pH and electrical conductivity, it becomes possible to identify the dominant factors contributing to water quality variations, predict potential water quality changes under different scenarios, and design appropriate mitigation measures to minimize environmental harm. Such models can serve as valuable tools for environmental monitoring, regulatory compliance, and decision-making processes related to mining activities. Hence, there is a need for laboratory modelling of pH and electrical conductivity of surface water from Maiganga Coal Mine and its implication on the environment.

Study area. ***Geographical location.*** The study area is located in Akko Local Government Area of Gombe State and bounded by Latitudes 11°07′46.44″E – 11°10′11.72″E" and Longitude 9°57′57.85″N – 9°59′41.08″N (Fig. 1).

The study area covers an area of 14.48 km^2 and is accessible by a major road from Gombe town to Kumo – Billiri town while secondary road from Kumo to the Maiganga to access the mine. Minor roads and footpaths link the various villages, settlements, and farmlands. The drainage pattern in Maiganga and its environs shows a dendritic pattern as can be seen (Fig. 2).

Methodology. ***Sample collection.*** Baseline data of Maiganga Coal mine was reviewed before carrying out in-situ (Fig. 3) measurement of physical parameters of surface water such as pH, Electrical Conductivity (EC), TDS and Temperature depending on availability within the coal mine and along the drainage/river channels using UNICEF standard procedure [10].

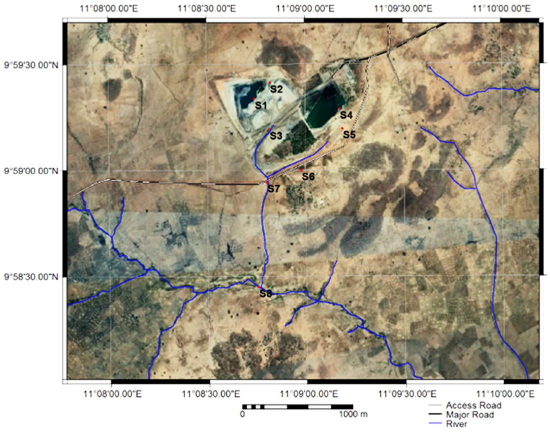


Fig. 1. Satellite image of the study area showing excavated land ponds and sample points within the coal mine (Google Earth 2023)

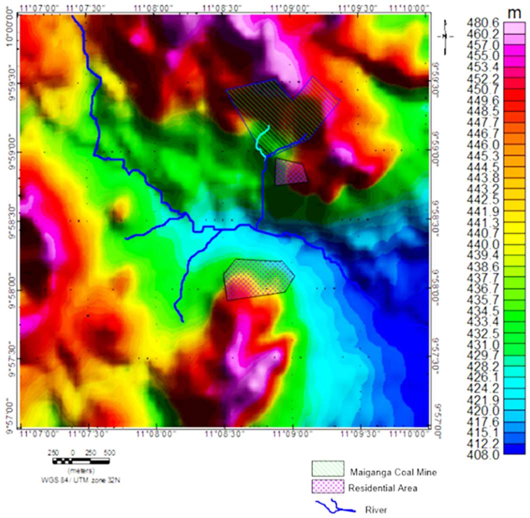


Fig. 2. Digital Elevation model and showing the drainage pattern of the study area

Fig. 3. Water samples collection points within and around Maiganga Coal Mine

Laboratory Modelling. Samples were first homogenized to form a composite or representative sample [11] and control samples were kept for comparison of the analyzed parameters. In order to get rid of other interference elements and matrix impacts [12], it was vital to choose and refine a digesting process for breaking down organic components and to transform the analyte into a form appropriate for analysis.

Modeling. Physical parameters were measured in-situ for all samples using an Oakton 5/6 pH/temperature meter and a TDS/EC meter. These parameters were temperature, total dissolved solids (TDS), electrical conductivity (EC), and pH [13]. A good understanding of fluid dynamics and contaminant transport principles to accurately simulate and interpret the results using Ansys Workbench 16.2 was observed in the following steps [14].

Geometry Creation: A geometry was created in ANSYS Design Modeler first by using the "Sketching" tab and selecting the appropriate sketching plane or face to create the geometry that can take care of the physical boundary of the drainage from the mine and upstream to show their reaction at the confluence before flowing downstream. Boundaries were created; two inlets were designed for the upstream and mine inlet while the third was an outlet for the downstream end. Other surfaces were left as wall in the geometry.

Mesh Generation: Generated a mesh that discretizes the geometric domain into small elements, allowing for fluid flow and contaminant transport calculations. The mesh was created using the default Ansys mesh generation software. A mesh of 507 nodes and 401 elements was automatically generated.

Setup: Set up the fluid flow simulation using the appropriate solver in Ansys Workbench, such as Ansys Fluent or Ansys CHF defined the boundary conditions, fluid properties, and any applicable fluid flow models. Ansys Fluent was used for the simulation and the setup was as follows:

Model: Viscous Standard K-Omega was used to capture the turbulence.

Materials: Water was selected as the fluid.

Boundaries Conditions: Boundary conditions in Ansys Workbench refer to the constraints or input conditions applied to a computational fluid dynamics model to simulate real-world operating conditions and obtain accurate results. These conditions define how the model interacts with its surroundings or how external forces are applied to the model. Mass flow-inlet was used for both the Mine inlet and Stream inlet, while Pressure outlet was used for the outlet (downstream). User defined scalars were used to represent the pH and Electrical Conductivity (EC) at the inlet.

Solution: SIMPLE was selected as the scheme for the simulation since it involves only simple scalar transport. Default solution control was used in the simulation. For the continuity, the residual for continuity was changed to 10^{-8} to enable the simulation run for accuracy.

Solution Initialization: Standard Initialization was used computed from the stream inlet.

Run Calculation: 1,000 iteration was inputted to allow the data to run smoothly before clicking on the calculation tab.

Post-Processing and Analysis: Analyze the simulation results using the post-processing tools Ansys Workbench (Contour and XY Solution tool) provided. This involves visualizing the contaminant concentration, examining flow patterns, and evaluating the impact of pollution on specific locations of interest along the flow direction.

Linear regression. A statistical method for simulating the linear relationship between the dependent variables and one or more regressors is called linear regression (LR). Using the ordinary least squares method, the linear regression is calculated to have the minimum possible sum of squares of the difference between the observed and predicted values in the current study [15]. The m-predictor linear regression model is displayed in Equation (1). The dependent variable in this equation is denoted by y, the independent variable (regressor) by x_j, the constant/intercept is β_j, the regression coefficient linked to each regressor is β_j, and the random error term is ε.

$$y = \beta_0 + \sum_{j-l}^{m} (\beta_j x_j) + \varepsilon.$$

Several statistical criteria need to be examined while creating a linear regression model in order to determine the model's

Table 1

In-situ reading of physico-chemical parameters collected from different locations

S/N	Parameters	S1	S2	S3	S4	S5	S6	S7	S8	Nigerian Standard for Drinking water [19]	WHO [20]
1	pH	2.3	1.5	2.9	5.5	3.5	8.4	3.2	4.3	6.5–8.5	6.5–8.5
2	TDS	398	3,491	458	300	454	85	514	389	500	300
3	EC	802	6,982	920	604	908	170	1,028	779	1,000	1,000

Table 2

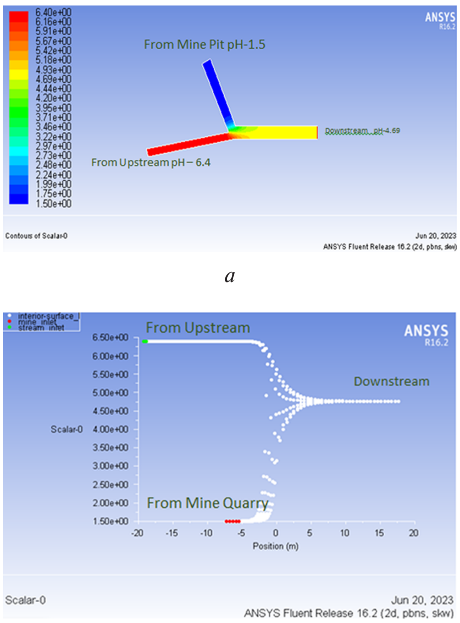
Descriptive statistics for water in Maiganga Coal Mine and Environs

Descriptive Statistics					
Parameters	N	Minimum	Maximum	Mean	Std. Deviation
pH	8	1.5	8.40	3.95	2.1686
TDS	8	85.0	3,491.0	761.13	1,110.96
EC	8	170.0	6,982.0	1,524.13	2,221.20
Valid N (listwise)	8	–	–	–	–

fitness for prediction [16]. The percentage of the endogenous variable's change that is described by the external variables is known as the coefficient of determination (R^2) [17]. Though the statistical significance of the R^2 depends on the degrees of freedom, a high R^2 does not necessarily indicate that the regression is appropriate for making predictions.

Results and Discussion. The results of pH, Electrical Conductivity and Total Dissolved solids of the water samples collected in the study area are presented in Table 1, all were collected within the ambient temperature [18]. Table 2 descriptive statistics and the graphical presentation of the data are in Figs. 3 to 7.

Modeling Using Ansys Workbench. Ansys Workbench is a powerful software platform that simulates and models various engineering and scientific problems. While it is primarily known for its structural, fluid dynamics, and electromagnetics simulations capabilities, it can also be used for modeling surface water pollution.



a

b

Fig. 4. Simulated result of pH conditions in water released directly from the mine to the main stream

Table 3

Response of downstream from the result of the mine inlet (pH & EC) from modeling in Ansys Workbench using Fluid Fluent tool

No	Mine (Inlet)	Upstream (inlet)	Downstream (outlet)	Mine (Inlet)	Upstream (inlet)	Downstream (outlet)
	Ph-in	–	Ph-out	EC-in	–	EC-out
1	1.5	6.4	4.76	1028	596	756
2	2.3	6.4	5.04	779	596	590
3	2.9	6.4	5.24	170	596	450
4	3.2	6.4	5.34	908	596	700
5	3.5	6.4	5.44	604	596	599
6	4.3	6.4	5.7	920	596	697
7	5.5	6.4	6.1	6,982	596	2,720
8	8.4	6.4	7.05	802	596	665

pH Simulated Data: Results of analysis and pH modeling from the mine effluent shows that the effluent coming from the mine is released directly without passing through the wetland, which could have an adverse effect on the downstream flow. Within the mine, the value of pH ranges from 1.5 to 2.3 which model with the upstream of pH value of 6.4 will have a confluence of 4.6, which is quite acidic and not good, which implies that the water is not fit for human and animal consumption. Mine drainage channel also had considerably low pH of 2.9–3.1 and, when simulated with the upstream gave a pH of 5.2 (weak acid) and still not good for drinking according to local and world standards [19–21]. Table 3, Figs. 4, 5 shows different pH models of measured points within and around the coal mine.

When the pH of water goes below 5.5 or rises above 8.5, harmful effects are evident. Coal is often associated with sulphur and other associated minerals; therefore, the acidic nature of the surrounding waters might be influenced by the reaction between sulphur and water to form sulphuric acid. As can also be observed in a certain well (sample S6), the acidic effect of the acidic water may have been offset by the composition of the surrounding soil, dissolved salts, and carbonates.

Electrical Conductivity Simulated data: Results of analysis and Electrical Conductivity (EC) modeling from the mine effluent shows that if the effluent coming from the mine is released directly without passing through the wetland, it will also have an adverse effect on the downstream. Within the mine the value of EC ranges from 802 to 6,982 µs/cm (Fig. 6 and Table 3) which when simulated with the upstream flow of value 594 µs/cm had a concentration of 3,523 at the confluence 3,523; this is not acceptable by the global standard as this will have a lot of dissolved elements (Heavy metals inclusive) and is not good for human and animal consumption. Mine drainage channel also had a considerable low EC of 920–1,056 µs/cm and when simulated with the upstream of 594 µs/cm gave an EC 750 µs/cm at the confluence, which good for drinking according to local and international standards [18, 19, 21]. Other

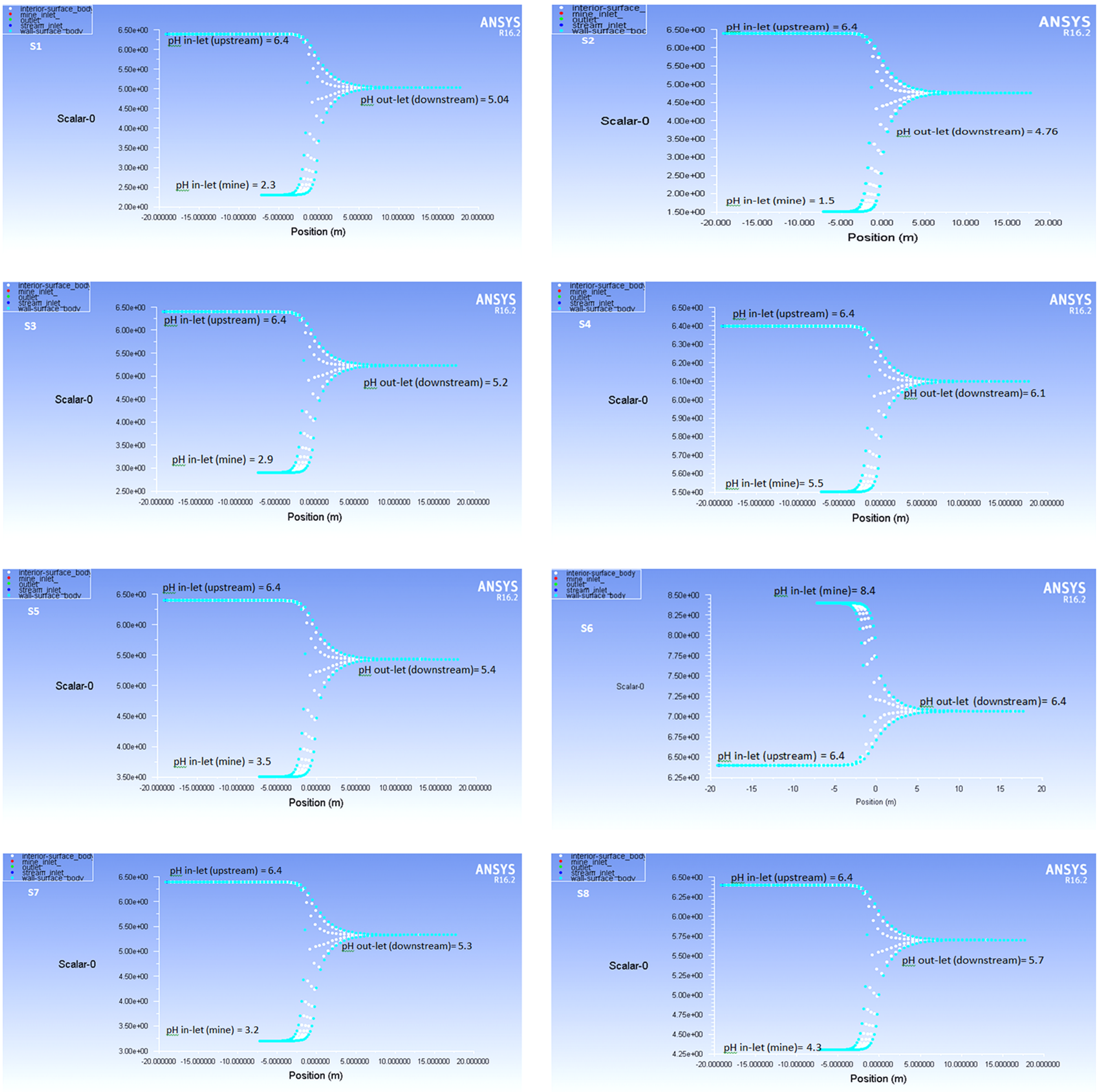


Fig. 5. Simulated data of various pH conditions measured in-situ in and around Maiganga Coal showing its interaction as it mixes with the upstream of pH -6.4 and the resultant outflow downstream in no preferred order

simulated data from different sample points are visible in Fig. 5 and their possible outcome can be viewed.

Higher EC values (1,028 and 6,982 µs/cm) were obtained from the mine pond and "yellow boy" respectively, implying that there are more dissolved elements in the water resulting possibly from the reaction of acidic water and surrounding rocks to form complexes. Elevated concentrations of these contaminants will result in increased conductivity, therefore determining the electrical conductivity of water is highly beneficial for industrial and environmental uses. It is imperative to note that water quality based on the EC values within the mine is not fit for domestic purposes according to WHO standards and Nigeria's standard for drinking water [19]. This might also not be suitable for industrial purposes in view of the excessively high values of EC.

Linear Regression : The adjusted R-square value of 1.000 in Tables 4 (pH) and 5 (EC) above indicates the independent variables (predictors); For example, the mine inlet utilized in this model demonstrates that the predictor is responsible for 100 % of the overall variation (downstream – Outlet). It indicates that the regression model can account for all of the dependent variable's fluctuation [22]. According to Achyut [23], the regression model is adequately explained by the adjusted R square, which is more than the benchmark value of 0.5. Table 4 demonstrates that the collinearity statistics show that all tolerance values exceed the literature benchmark, indicating that the eight independent variables are independent of one another and confirming the suitability of carrying out the regression analysis.

Tables 4 and 5 of Anova are both significant since p-value/Sig value is less than 0.05. In the tables, it is 0.000. The F-ratio indicates how well the model fits the variable while taking into account the model's inherent imperfection. An F-ratio yields efficient model with a value greater than 1. The above table shows 75,801.013 for pH and 131,201.005 for EC respectively, which is good. For the reason that the significant value of 0.000 is less than the permissible value of 0.05, the coefficients in the Tables demonstrate the substantial change in the dependent variable caused by anthropogenic activities. The pH and EC rate will rise in response to a 1 % increase in mining activity. Thus, the data indicates that there is a strong positive correlation between mining operations and the pH and EC concentration downstream.

It appears that the error terms are normally distributed based on the residuals' normal probability plot. The residuals' departure from the normal line is depicted in Figs. 6 and 7. The scatters should lie on or very near the normal distribution line in order for the Standardized residuals to be normally distributed. The residuals' scatters essentially lie linearly on the normal distribution line in Figs. 6 and 7 (pH and EC, respec-

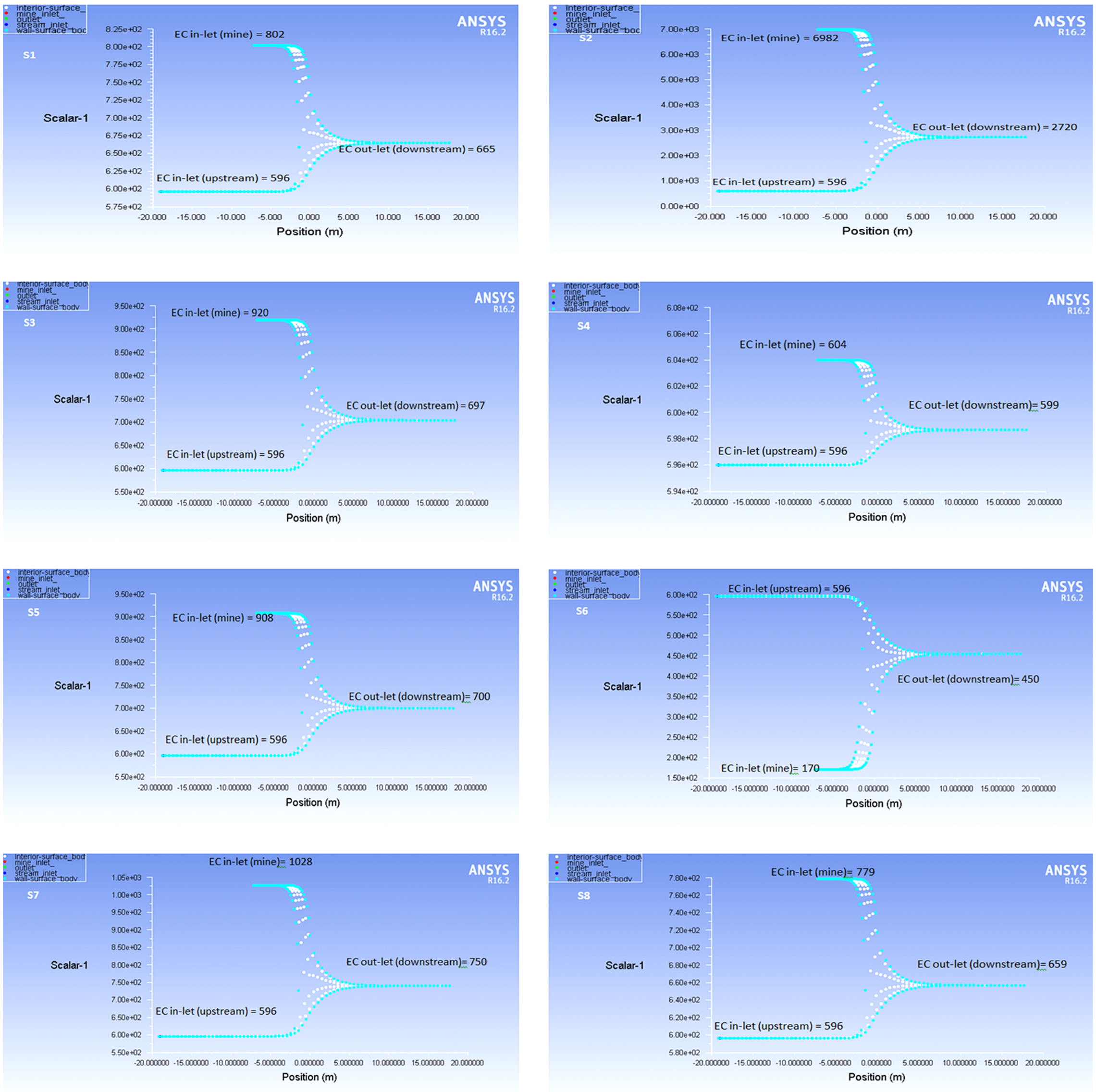


Fig. 6. Simulation result of Electrical Conductivity if water flow is considered directly from the mine

tively), suggesting a normal distribution of residuals [24]. The graph above demonstrates that there is not a significant residual deviation from the normal line. It is also evident that the data set passes through the origin. Therefore, it suggests that the residuals have a roughly normal distribution. As a result, it can be said that the observed data has a normal distribution.

Effect on Water Quality: The main objectives following the in-situ assessment of pH and EC is to determine the surface and ground water quality and its impact on the environment. Preliminary investigation shows that the pH was slightly alkaline (7.8–8.6) within the surrounding water bodies before the inception of the mine. However, with the commencement and progression of mining activities, the pH values of surface water within the mine now range from 1.5 to 5.4. According to the World Health organization [18] and Nigerian Standard for Drinking water quality (NSDWQ) [19], the range of desirable pH values of water for drinking purposes is 6.5–8.5. In this study, only water from the resettled Maiganga Village well south-east of the mine had a pH of 8.4 but the mine drainage had a pH of 3.2. The water pH in the mine drainage was far above the maximum permissible limit for drinking water quality, it is not good for drinking. Also, the pH is not within the range for optimal plant growth and productivity because a pH range of 5.5–6.5 is optimum for plant growth [25]. Other than for dairy cattle, the ideal pH range for animal water is 5.5 to 8.3. Extremely alkaline water can lower feed/water intake, induce diarrhea, disturb the digestive system, and have a negative feed conversion Other than for dairy cattle, the ideal pH range for animal water is 5.5 to 8.3. Extremely alkaline water can lower feed/water intake, induce diarrhea, disturb the digestive system, and have a negative feed conversion [26], therefore, the water within and around the mine though used by cattle for drinking is however, not suitable.

Electrical Conductivity (EC) within the mine drainage channel ranged from 802 to 1,056 μs/cm, rendering it unfit for domestic purposes and animal consumption. In addition, the cloudy nature of the water renders it unfit for drinking and other uses.

Effect on Environment: Low pH levels in bodies of water, such as lakes, rivers, and oceans, can harm aquatic organisms [27]. Many aquatic species, including fish, amphibians, and invertebrates, have specific pH tolerances. Acidic conditions can disrupt their physiological functions, impair growth, reproduction, and survival [28]. Low pH can also release toxic metals like aluminum and mercury from sediments harming aquatic life [29].

Biodiversity Loss: The acidification of ecosystems can disrupt ecological balances and lead to biodiversity loss. Acidic conditions may favor certain organisms that are more tolerant of low pH, while other species decline or disappear. This can result in shifts in species composition and disrupt the intricate web of ecosystem interactions [30].

Table 4

A model summary for pH when released from the mine (data generated from Table 3)

Adjusted R-Square					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	1.000[a]	1.000	1.000	0.00689	
a. Predictors: (Constant), Mine (Inlet)					
b. Dependent Variable: Downstream (outlet)					

Anova[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.602	1	3.602	75,801.013	0.000[b]
	Residual	0.000	6	0.000	–	–
	Total	3.602	7	–	–	–

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.277	0.005	–	801.710	0.000
	Mine (Inlet)	0.331	0.001	1.000	275.320	0.000
a. Dependent Variable: Downstream (outlet)						

Residuals Statistics[a]					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.7733	7.0558	5.5838	0.71735	8
Residual	–.01332	0.00510	0.00000	0.00638	8
Std. Predicted Value	–1.130	2.052	0.000	1.000	8
Std. Residual	–1.933	0.740	0.000	0.926	8
a. Dependent Variable: Downstream (outlet) b. Predictors: (Constant), Mine (Inlet)					

Table 5

A model summary for EC when released from the mine (data generated from Table 3)

Adjusted R-Square					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	1.000[a]	1.000	1.000	5.397	
a. Predictors: (Constant), Mine (Inlet)					
b. Dependent Variable: Downstream (outlet)					

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3,822,141.208	1	3,822,141.208	131,201.005	0.000[b]
	Residual	174.792	6	29.132	–	–
	Total	3,822,316.000	7	–	–	–
a. Dependent Variable: Downstream (outlet) b. Predictors: (Constant), Mine (Inlet)						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	397.966	2.367	–	168.157	0.000
	Mine (Inlet)	0.333	0.001	1.000	362.217	0.000
a. Dependent Variable: Downstream (outlet)						

Residuals Statistics[a]					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	454.52	2,720.68	905.00	738.932	8
Residual	–7.024	10.047	0.000	4.997	8
Std. Predicted Value	–.610	2.457	0.000	1.000	8
Std. Residual	–1.301	1.861	0.000	0.926	8
a. Dependent Variable: Downstream (outlet)					

Conclusion. The activities of coal exploitation in Maiganga area had initiated the comparative modeling using Ansys Workbench and water quality analysis between the two analyzed parameters (pH and Electrical Conductivity (EC)) which indicates mine effluent influence. The high values of pH and EC gotten from the flowing water channels shows that the surface water source of pollution is primarily from the Mine.

From the regression statistics model of pH and EC, the predicted values have a minimum value of 4.7 pH and 454.52 µs/cm (EC), a maximum value of 7.05 pH and 2,720.68 µs/cm (EC) and a mean of 5.5 pH and 905 µs/cm (EC) for the downstream flow which is completely dependent on the mine inlet (pH-in and EC-in). It is important to note that the primary driver of the low pH in the environment is anthropogenic activities (mining). Reducing these sources of acidity through pollution control measures and sustainable practices is crucial for mitigating the harmful effects of low pH on the environment.

Overall water quality has been degraded by the mining activities ongoing within the community. Therefore, continuous water monitoring of water quality is required to identify necessary action to be taken for mitigation.

With the models of this study, stakeholders can assess the potential risks associated with mining operations, design effective monitoring and control strategies, and develop mitigation measures to protect water resources and minimize environmental harm. This will go a long way in enhancing the Sustainable development goals (Goal No. 3; Good Health and Well-being, Goal No. 6; Clean water and sanitation, Goal No. 7; Affordable and Clean Energy and Goal No. 14; Life on Land) [31, 32].

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Моделювання змін pH та електропровідності поверхневих вод унаслідок гірничодобувної діяльності

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Мета. Розробити комплексні моделі для прогнозування pH та електропровідності поверхневих вод у вугільній шахті Майганга та на прилеглих територіях, що постраждали від гірничої діяльності.

Методика. У дослідженні використовується поєднання вимірювань на місці, лабораторного аналізу, методу моделювання з використанням комплексу Ansys Workbench і лінійної регресії для прогнозування вмісту забруднюючих речовин. Вимірювання на місці/збір даних у верхній і нижній частинах течії були проведені з метою оцінки потенційного впливу гірничих робіт на якість поверхневих і підземних вод. Електропровідність і pH вимірювали на зразках, що були зібрані за допомогою pH-метра Oakton 5/6 і приладу для вимірювання загальної мінералізації води/електропровідності (TDS/EC-метра).

Результати. За результатами, модель регресійної статистики pH та електропровідність (ЕП) показує, що прогнозовані значення мають діапазон pH 4,7–7,05 і середнє значення pH 5,5. Навпаки, ЕП коливається від 454,52 до 2720,68 мкс/см із середнім значенням 905 мкс/см потоку вниз за течією, що повністю залежить від входу до шахти (вхідний pH і ЕП на вході). Отримані дані показують пряму залежність між рівнем pH поверхневих вод, електропровідністю та гірничодобувною діяльністю в районі вугільної шахти Майганга та її шкідливим впливом на екосистему та якість води.

Наукова новизна. Результати були отримані безпосередньо на шахті під час польового візиту і їх можна порівняти з даними з діючих вугільних шахт.

Практична значимість. Негативний вплив результатів гірничодобувної діяльності можна контролювати, якщо встановити датчики моніторингу на виході шахтних стоків, щоб попередити керівництво шахти про можливу небезпеку в режимі реального часу.

Ключові слова: *шахта Майганг, pH, електропровідність, прогнозне моделювання, поверхневі води, екологічний моніторинг*

The manuscript was submitted 09.10.23.