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## Regression of Chemical Oxygen Demand and Total Organic Carbon In Selected Mining Polluted Groundwater Sources

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### Abstract

Groundwater constitutes a critical source of freshwater for domestic and agricultural use in many rural and semi-urban communities across developing countries. However, the contamination of these vital resources by mining activities has emerged as a growing global environmental challenge. This study investigates the relationships between Total Organic Carbon (TOC), colour, turbidity, microbial load, and Chemical Oxygen Demand (COD) in groundwater impacted by mining activities, with the objective of enabling rapid water-quality assessment, determining pollution levels, and identifying appropriate treatment options. Groundwater samples were collected from wells and boreholes across selected Local Government Areas in Osun State between July 2024 and May 2025 in order to capture spatial variations in water quality. The collected samples were subjected to comprehensive physicochemical and microbiological characterization. Empirical relationships between COD and selected water-quality parameters (TOC, colour, turbidity, and microbial load) were developed using both first-order and second-order models. These models were solved using matrix functions in Microsoft Excel and the results were compared with outputs generated using the Microsoft Excel Solver (MES). For the first-order model, the regression coefficients for TOC, microbial load, colour, and turbidity were 2.7687, -0.0022, 4.5262, and 0.0831, respectively, using the matrix approach, and 2.8321, -0.0047, 2.0835, and 0.0559, respectively, using the MES technique. Statistical evaluation using analysis of variance (ANOVA) showed no significant difference between the coefficients obtained from the two methods at the 95% confidence level ( $F_{1,6} = 0.2109$ ,  $p = 0.6622$ ). Similar trends were observed for the second-order model, further confirming the robustness and consistency of the modeling approaches. Overall, the results demonstrate a strong correlation between TOC and COD, indicating that TOC can serve as a reliable predictor of Chemical Oxygen Demand in mining-contaminated groundwater. This finding provides a practical and cost-effective basis for rapid assessment of organic pollution and supports informed decision-making for groundwater management and treatment in mining-impacted regions.

### Keywords

Microsoft Excel Solver, Matrix Functions, Groundwater sources, Water Quality Assessment, Chemical Oxygen Demand

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## 1. INTRODUCTION

Guaranteeing affordable and safe potable water is essential for human wellbeing and public health (Pervin et al., 2008; Nnorom et al., 2019; Assefa et al., 2024). Access to and availability of clean and potable water serves as a obstruction against the epidemic of waterborne and water related diseases triggered by the presence of microorganisms and vectors in both surface and groundwater sources, but in addition plays a serious role in safeguarding the continuing availability and accessibility of surface and groundwater resources for the public health and wellbeing of next generations (Assefa et al., 2024 ; Etisa et al., 2024; Wang et al., 2025; Hartz et al., 2025).

Though, surface and groundwater are the main sources of drinking water in developing countries after selected treatment techniques and processes, the frequent problem of water contamination and pollution remain major challenges with common effects on ecosystems and human wellbeing (Assefa et al. 2024). TOC, Chemical Oxygen Demand (COD), turbidity, colour, and pH of groundwater are crucial factors for the quality of the ecosystem (Kuznietsov and Biedunkova, 2024). The impact of the water quality pollutants on water bodies can meaningfully affect the aquatic environment and its biota (Mamun et al., 2022; Makumbura et al., 2024).

In spite of its general utilization COD, BOD<sub>5</sub> and TOC in water quality indices and evaluating the efficiency of wastewater treatment plants, COD and BOD<sub>5</sub> analyses have several disadvantages like time-consuming, being inexact, creation of hazardous solid and liquid wastes and insensitive these parameters to pollution level (Kim and Jo, 2016; Jiao et al., 2021).

TOC, which is known to be the quantity of carbon established as organic compounds or composition of a sample and aa a key parameter utilised to evaluate the organic contamination, pollution or organic content in soil, water, sediments, or other substances (Gu et al., 2015; El Mourabit et al., 2020; Wu et al., 2022), can be utilised as an alternative analysis for accurate results and to eliminate the disadvantages of BOD<sub>5</sub>, COD determinations. The organic carbon in water and wastewater originates from a variety of organic compounds in various oxidation states.

Some of these carbon compounds can be oxidized through chemical or biological processes. Wojnárovits et al. (2024) listed different types of TOC as both conventional and emergency pollutants in water as natural water contaminants as Dyes, Pesticides, Miscellaneous drugs, non-steroidal anti-inflammatory drugs, Blood pressure regulators, Macrolides,  $\beta$ -Lactam antibiotics, Tetracyclines, Fluoroquinolones, Sulphonamides and Laboratory chemicals.

The advantages of TOC over COD are a short time procedure, accurate results, low production of toxic substances like mercury, not affected by hindering substances and reliable. Although, there are previous studies like Bhat et al. (2003); Siwec et al. (2012; 2018), Cossu et al.(2012); Hocaoglu and Orhon (2013); Lee and Nikraz (2014); Abdalla, and Hammam (2014), Lee and Nikraz (2015), Jin et al. (2015), Szaja et al. (2015), Scholeset al. (2016), Kim and Jo (2016), Jiao et al. (2021); Liu et al. (2022), Liu et al. (2023), Sodikin et al. (2025), Elgalabwater, (2025); Nuraya and Agawaman (2025) and Gong et al. (2025) on ratio and relationship between COD, BOD and TOC, but literature

and information on the possibility of utilising TOC to express the strength of groundwater rather than of COD and BOD<sub>5</sub> is little, which can be attributed to the challenging in an accepting correlation between TOC, other water quality parameters and COD. Hence, this study.

## 2. LITERATURE REVIEW

Groundwater is an important source of water supply in both rural and urban communities. Groundwater transports organic matter (OCM) in the soil from surface water runoff to the water table as well as to the aquifer. Groundwater is a critical mechanism of the global hydrological and carbon cycles (El Mourabit et al., 2020). COD, TOC, and Biochemical Oxygen Demand (BOD<sub>5</sub>) can be considered balancing methods for monitoring OCM content in water bodies and wastewaters (Jouanneau et al., 2013; Geerdink et al., 2017; Li et al., 2018; Hassan et al., 2021; Lopes et al., 2022; Doaemo et al., 2023; Kumar et al., 2024). BOD<sub>5</sub> stands for the quantity of oxygen demand required by microorganisms in water and wastewater to decompose all the OCM present.

COD is the amount of oxygen needed or a reflection of the quantity of oxygen consumed or utilised by the specific chemicals in the decomposition of OCM in water and wastewaters. TOC represents the concentration or amount of carbon dioxide produced or generated during the catalytic combustion of OCM in wastewater and water. Aguilar-Torrejón et al. (2025) reported that the quantities of COD, BOD<sub>5</sub>, and TOC are functions of the type and selected water quality parameters of the water and wastewater. BOD<sub>5</sub> and COD are the most reliable and accurate amount of increase in the amount of OCM that are available for

oxidization processes utilising either biological or chemical processes (Costa et al. 2018). It has been recommended that these selected water quality parameters should be used together with other water quality parameters to assess or evaluate organic pollution in water bodies. It has been documented that COD values and magnitudes are generally higher than BOD<sub>5</sub> values and it depends on the type of water analysed (Recoules et al. 2019). Determining the chemical oxygen demand (COD) is challenging because of the chemicals that are used in the current methods. There is an urgent need to determine the pollution in groundwaters from (heavy) industry through a simple, reliable, and fast method (Geerdink et al., 2017; Hsiang et al., 2019; Ukaogo et al., 2020).

Figure 1 presents the historical view of the development of the COD determination. BOD<sub>5</sub> correlates with the quantity of microorganisms and microbial pollution. TOC is the quantity of all types of OCM in wastewater and water (Si et al., 2019). Wojnárovits et al. (2024) expressed theoretical oxygen demand, which is the stoichiometric amount of Oxygen needed to oxidise any organic carbon of C<sub>c</sub>H<sub>h</sub>Cl<sub>cl</sub>N<sub>n</sub>Na<sub>na</sub>O<sub>o</sub>P<sub>p</sub>S<sub>s</sub> to carbon dioxide, ammonia, phosphate and water as follows:

$$OD_t = \frac{16[2c + 0.5(h - cl - 3n) + 3s + 2.5p + 0.5na - o]}{M}$$

Where, *M* is the molecular mass of the organic carbon and *OD<sub>t</sub>* is the theoretical oxygen demand.

Despite the utilisation of toxic substances, chemicals, and reagents for COD and a very long period of time for analysis needed for BOD<sub>5</sub> (5 days), these techniques, methods, procedures and water quality parameters

(BOD and COD) are widely utilised and have not been completely substituted by other measurements (Aguilar-Torrejón et al., 2023). In addition, with establishment of emerging pollutants like Benzamine, 2,6-Dichloraniline, p-Aminophenol, m-Aminophenol, o-Aminophenol, Chlorobenzene, 2,4-dichlorophenol, p-Chlorophenol, m-Chlorophenol, o-Chlorophenol, p-Cresol, m-

Ciprofloxacin, Sulphisoxazole, Sulphathiazole, Sulphadiazine, Sulphacetamide, Sulphanilic acid in groundwater there is a need to remove these harmful pollutants (Zak et al., 2021, Kuznietsov et al., 2024, Zuo et al., 2023) measure TOC as a replacement

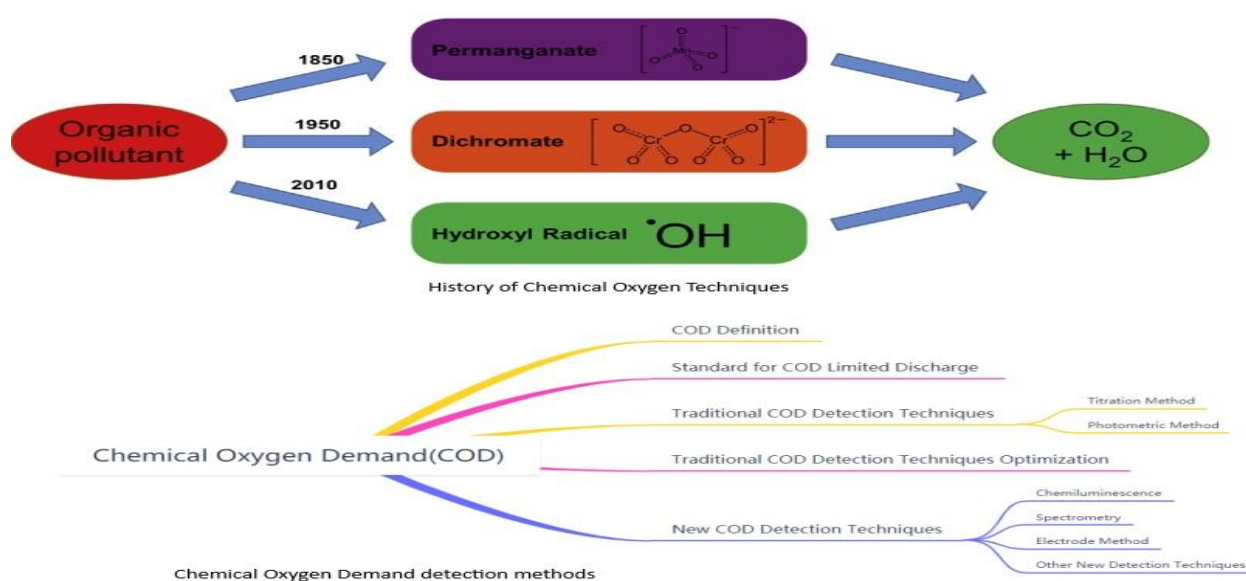


Figure 1 History of COD techniques and classifications of the techniques (Source: Geerdink et al., 2017; Wu et al., 2022).

Cresol, o-Cresol, 4-Hydroxyanisol, Phenolate, Phenol, Benzoic acid, Triton X-100 Cyclohexanone, Fumaric acid, Maleic acid, Vinyl acetate, Ethylene glycol, Isopropanol, 2,4-Dichlorophenoxy-acetic acid, Buturon, Linuron, Monolinuron, Diuron, Monuron, Fenuron, Chloramphenicol, Amodiaquine, Clofibric acid, Salicylic acid, Acetylsalicylic acid, 5-Sulfo-salicylic acid, Ketoprofen, Diclofenac, Paracetamol, Atenolol, Nadolol, Propranolol, Labetalol, Acebutolol, Clarithromycin, Azithromycin, Erythromycin, Piperacillin, Cloxacillin, Oxacillin, Amoxicillin, Oxytetracycline, Doxycycline, Chlortetracycline, Tetracycline, Ofloxacin, Norfloxacin,

for COD.

Although, there are previous studies like Bhat et al. (2003); Siwiec et al. (2012), Cossu et al. (2012); Hocaoglu and Orhon (2013); Lee and Nikraz (2014); Abdalla, and Hammam (2014), Lee and Nikraz (2015), Jin et al. (2015), Szaja et al. (2015), Scholeset al. (2016), Kim and Jo (2016), Jiao et al. (2021); Liu et al. (2022), Liu et al. (2023), Sodikin et al. (2025), Nuraya and Agawaman (2025) and Gong et al. (2025) on ratio and relationship between COD, BOD and TOC, but literature and information on the possibility of utilising TOC to express the strength of groundwater rather than of COD and BOD<sub>5</sub> is little, which

can be attributed to the challenging in an accepting relationship between TOC, other water quality parameters and COD. The key aim and objective of this study is to develop a relationship between COD, TOC, Turbidity, colour, and microbial concentrations as a tool

**MATERIALS AND METHODS:** Water samples were collected from 6 groundwater sources (Table 1 and Figure 2) in two Local Government Areas (Atakumosa West and Atakumosa East) in Osun State (between July 2024 and May 2025). The water quality (TOC, Chemical Oxygen Demand (COD), Turbidity, colour, pH, Total alkalinity, sulphate, hardness, chloride, cadmium, lead, total dissolved solids, salinity and nitrate) of these collected water samples was determined utilising standard methods and techniques as stated in APHA (2019), Van Loosdrecht *et al.* (2016); Van Loosdrecht, *et al.*, (2016). Kafle (2019).

The relationship between COD and other selected water quality parameters (TOC, Colour, Turbidity, Microbial load) was established utilising correlation function, the first order (Equation 1), and second order (Equation 2) without interception utilising Matrix functions in Microsoft Excel (MFMF) and compared with results from Microsoft Excel Solver (MES) technique statistically utilising Analysis of Variance to

for quick assessment of the pollution level of groundwater and to evaluate the relationship utilising statistical techniques.

ascertain accuracy of the system. Figures 3 and 4 present the flowchart of the two techniques.

$$Y = \alpha_i \sum_{i=1}^N X_i \quad (1)$$

$$Y = \alpha_i \sum_{i=1}^N X_i + \alpha_{ij} \sum_{ij=1}^N X_i X_j \quad (2)$$

Where: Y is the concentration of COD;  $\alpha_i$  is the coefficient of the water quality parameter  $X_i$  and  $X_i$  is the water quality parameter. The detailed equations, detailed least square equations, matrix, inverse of the matrix and solution of the equations are presented at the Appendix.

Table 1: Location of the Sampling points

TOWN LOCATION	Iyere dug well	Iyere PHC borehole	Iloro dug well, Iperindo
Global Positioning System	N7°34'0.96'' E4°39'17.57''	N7°34'1.48'' E4°43'9.55''	N7°30'6.59'' E4°49'35.20''
TOWN LOCATION	Borehole, Imagboro	Araromi Ogbontuntun Borehole, Odo-Ijesa	Iloro Borehole, Iperindo
Global Positioning System	N7°32'25.86'' E4°49'44.47''	N7°31'36.88'' E4°49'17.20''	N7°30'1.14'' E4°49'34.85''



Figure 2a: Location of Araromi Ogbontuntun Borehole Sampling Point



Figure 2b: Location of Borehole Imagboro Sampling Point

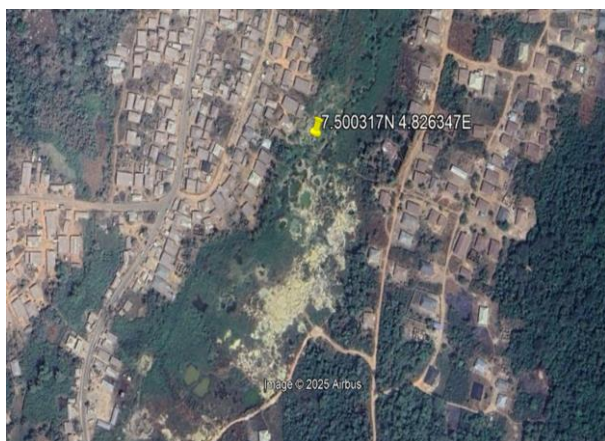


Figure 2c: Location of Iloro Borehole Iperindo Sampling Point

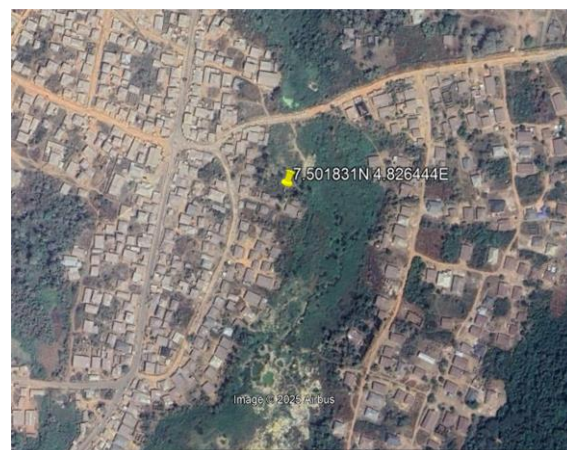


Figure 2d : Location of Iloro duawell Iberindo Samblina Point

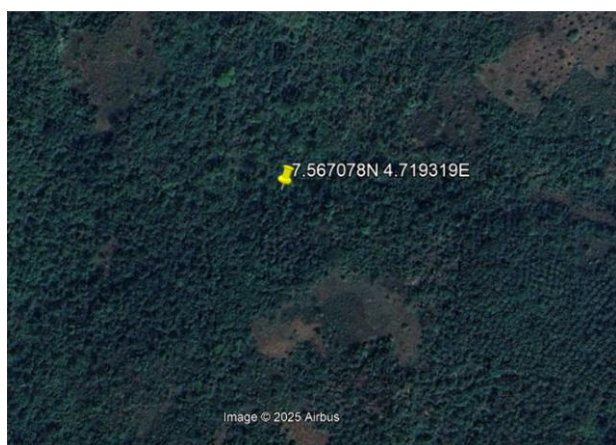
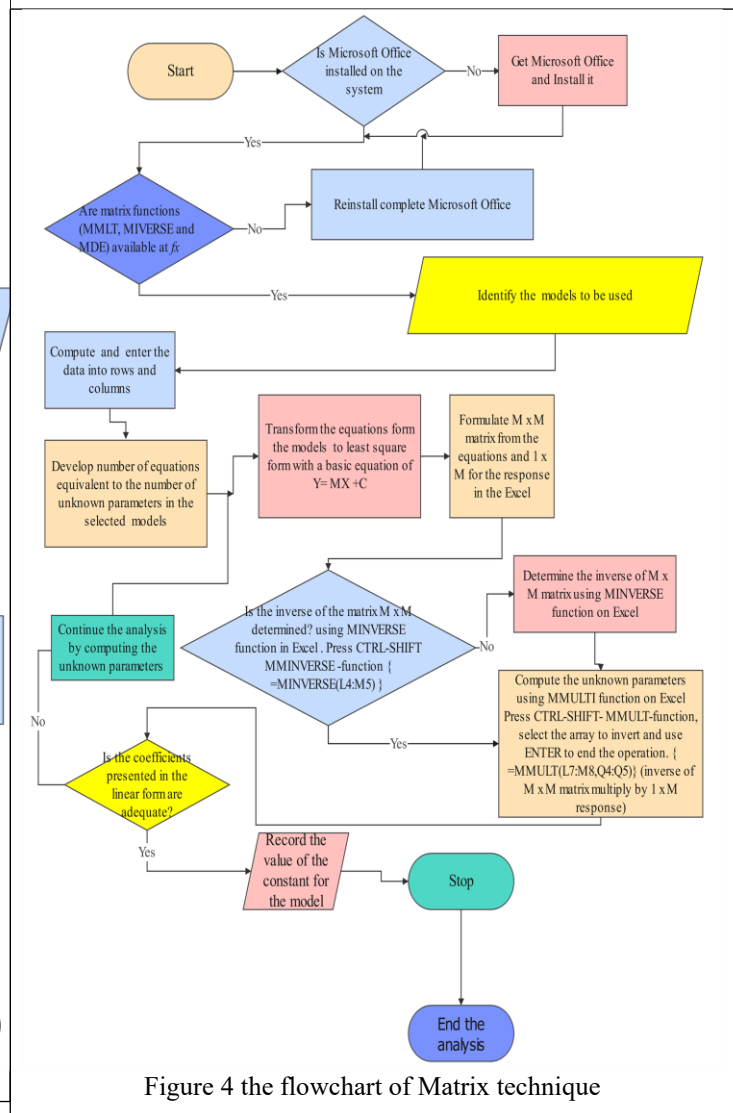
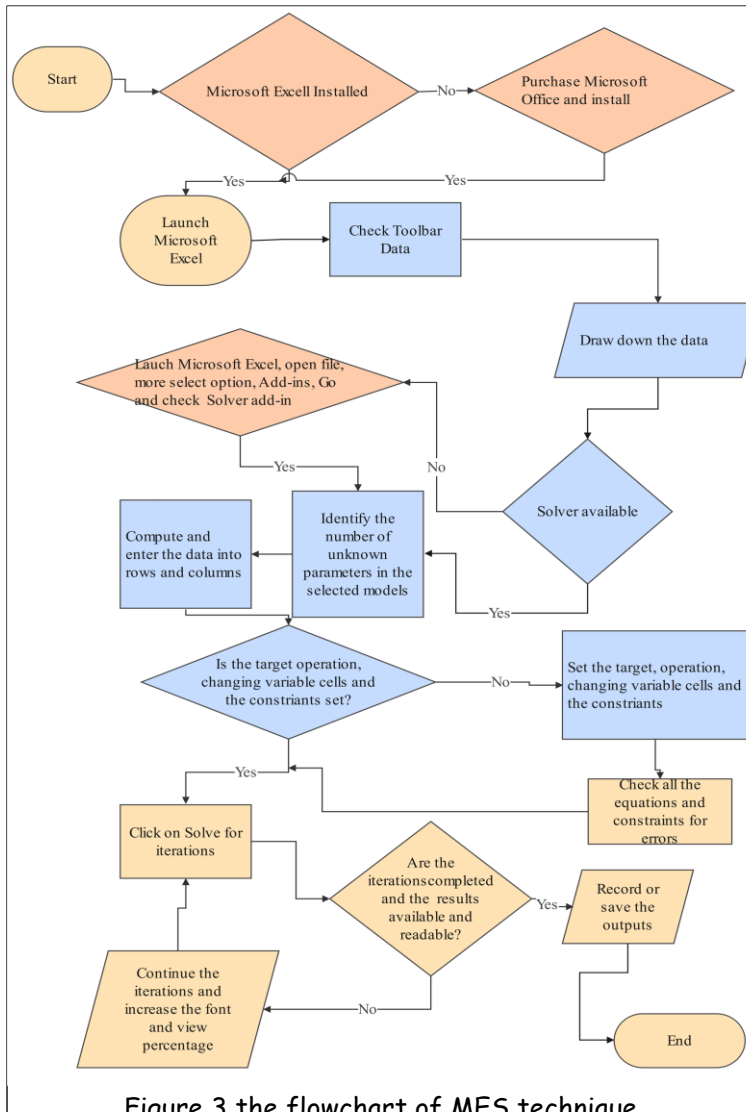


Figure 2e: Location of Iyere PHC borehole Point



Figure 2f: Location of Iyere dugwell Sampling Point



## RESULTS AND DISCUSSION

Table 2 presents the statistical information and data on the selected water quality parameters. The Table established that hand-dug wells present lower quality water of COD (503.31 mg/l) and turbidity (208 .07 NTU) than borehole sources, which may be attributed to the deep and higher depth of the filtration mechanism by the soil. In the case of Colour and Microbial load, some boreholes (Borehole, Odo-Ijesa, Borehole, Imogbara, Iyere Borehole, Iyere, and Borehole at Palace, Iloro Iperindo) had the poorest water quality, which can be attributed to environmental factors like colour development composition in the soil, leachate colour materials, and

microorganisms. In addition, the Table revealed that the concentrations of TOC were higher in both boreholes and hand-dug wells (between 172.37 mg/l and 173.28 mg/l).

These higher concentrations can be attributed to vital organic contamination from sources like vegetation decay, microbial activity, or human activities, which is signals potential water quality concerns that may require additional treatment, can lead to the formation of harmful disinfection byproducts (DBPs) like trihalomethanes, makes treatment of the water source more challenging by increasing chemical demand and reducing treatment efficiency (Christian et al., 2017; Health Canada, 2020; Alewi et

al., 2022; Crini et al., 2024). However, variation in the concentrations of COD and TOC in these water samples can be attributed to several factors, like types of TOC, composition of the soil, environmental factors and human activities (Kang et al., 2019; Senoro et al., 2023; Lacalamita et al., 2024; Tomczyk et al., 2025; Sáez-Ardura et al., 2025).

Figure 5 presents the types and composition of TOC. Table 3 presents the result of the correlation between COD and selected water quality parameters in respect to the first-order model (correlation evaluation). The Table revealed that there is negative correlation between TOC (-0.73357), colour (-0.49728) and COD, while Microbial load (0.410133, CFU/100 ml) and Turbidity (0.642374) have a positive correlation. Table 4 shows the statistical evaluation of the regression analysis of the First Model (significant test of the selected factors). The Table established that TOC is a vital factor in the correlation of COD with water quality parameters (coefficient of 2.823345, p-value of 0.00261 and t-statistical value of 19.53487).

In addition, the Table revealed that the other selected factors (Microbial load, Colour and Turbidity) are statistically vital at a 95 % confidence level (p-values of 0.952265, 0.775991, and 0.441882, respectively. P greater than 0.05). The Table revealed through *regression statistics* that the correlation coefficient of the regression was 0.999985 and correlation coefficient (R Square) was 0.999969. Table 5 shows ANOVA of Regression analysis of First Model, which established that the regression was vital expression ( $F_{2,4} = 16309.36$  and  $p = 0.005873$ , which indicate that p is less than 0.05). Table 6 presents the result of the

correlation between COD and selected water quality parameters in respect to the second-order model. The Table revealed that the vital factor that relates to COD strongly was  $X_1$  (TOC) with correlation coefficient of -0.7336, while the vital interaction factor that relate to COD strongly was  $X_5$  (TOC and TOC) with correlation coefficient of -0.7335.

In addition, the Table established the moderate vital factors and interaction factors as  $X_4$  (Turbidity),  $X_8$  (TOC and Turbidity),  $X_{11}$  (Turbidity and Turbidity),  $X_{13}$  (Microbial Load), and Turbidity, NTU), and  $X_{14}$  (Colour and Turbidity) with correlation coefficient of 0.6424, 0.6423, 0.6489, 0.6490 and 0.6414. These results indicate that TOC can be utilized to predict COD in water and wastewater.

Table 7 shows coefficients of the water quality parameters in relation to COD for the two models (first and second orders). The table revealed that for First Order model the regression coefficient was between -0.0005 for  $X_2$  (Microbial load, CFU/100 ml) with 2.823 for  $X_1$  (TOC), utilising MES techniques and between -0.0022 for  $X_2$  (Microbial load, CFU/100 ml) and 4.5262 for  $X_3$  (Colour) utilising the Matrix technique.

These results established that the presence of microbial influences relationship between COD and TOC negatively, which indicates that the impacts of the factor (presence of microbial load) must be looked into. In the case of Second order model, the Table revealed that some factors and interactions ( $X_1$ ,  $X_5$ ,  $X_6$ ,  $X_7$  and  $X_8$ ) are essential in the relationship between COD and TOC. These results revealed that TOC is an essential factor in the relationship of COD, which indicates the TOC can be used to predict COD based on these relationships. Table 8

and 9 show ANOVA of regression coefficient analysis of First and Second order models, respectively, for the two techniques utilized. These tables revealed that there were no statistical differences between regression coefficient (First and Second order models), simulated COD and experimental COD at a 95 % confidence levels ( $F_{1,6} = 0.210928$  and  $p = 0.66221$ ;  $F_{1,26} = 1.9987623$  and  $p = 0.1692902$ ). Figure 6: Relationship between simulated and experimental COD utilising TOC only and first order model. The figure revealed that there is an excellent relationship between TOC only and COD, which indicates that TOC can be used to predict COD concentration of groundwater

Table 2: Statistical summary of the selected parameters

Water Sources	COD (mg/l)	TOC (mg/l)	Microbial load (CFU/100 ml)	Colour (Colour Unit)	Turbidity (NTU)
Borehole at Palace, Iloro Iperindo	496.17	173.27	980.00	4.09	7.41
Iyere Borehole, Iyere	501.74	172.86	279.00	4.09	7.41
Iyere Dugwell, Iyere	503.31	172.37	973.00	2.65	208.07
Borehole, Imogbara	498.68	173.26	320.00	4.09	7.41
Dug well, Iloro Iperindo	497.47	173.28	284.00	3.04	36.49
Borehole, Odo-Ijesa	493.27	173.09	48.00	4.09	7.41
Limit	5.00	2.00	0.00	5.00	5.00
Mean	498.44	173.02	480.67	3.67	45.70
Standard Deviation	3.67	0.36	396.00	0.65	80.39
Skewness	0.004	-1.518	0.690	-1.116	2.342
Kurtosis	-0.79	1.88	-1.70	-0.99	5.54

Table 3: Result of correlation between COD and selected water quality parameters in respect of first order model

Description	COD	TOC	Microbial load (CFU/100 ml)	Colour	Turbidity
COD	1				
TOC	-0.73357	1			
Microbial load (CFU/100 ml)	0.410133	-0.40114	1		
Colour	-0.49728	0.56226	-0.38642	1	
Turbidity	0.642374	-0.85324	0.584724	-0.85049	1

Table 4 Statistical evaluation of regression analysis of First Model

Description	Coefficients	t Stat	P-value	Regression Statistics	
TOC	2.823345	19.53487	0.00261	Multiple R	0.999985
Microbial load (CFU/100 ml)	-0.00047	-0.06758	0.952265	R Square	0.999969
Colour	2.071408	0.325057	0.775991	Adjusted R Square	0.499923
Turbidity	0.055815	0.951234	0.441882	Standard Error	4.780173

Table 5 ANOVA of Regression analysis of First Model

Source of Variation	Sum of Squares	Degree of freedom	Mean Sum of square	F-value	P-value
Regression	4	1490679	372669.7	16309.36	0.005873
Residual	2	45.70011	22.85005		
Total	6	1490725			

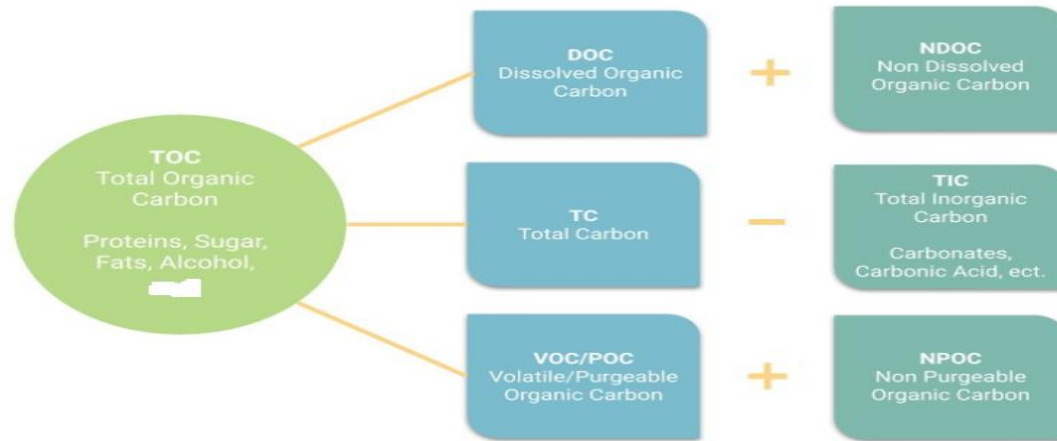


Figure 5 types and composition of TOC (Source: Aguilar-Torrejón, et al., 2023).

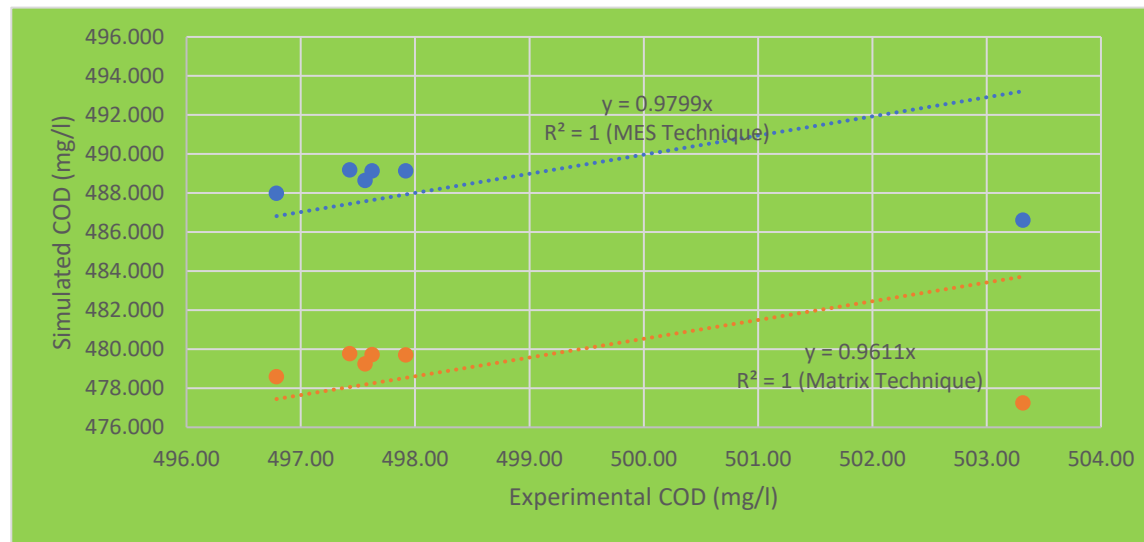


Figure 6: Relationship between simulated and experimental COD utilizing TOC only and the first-order model

Table 6 : Result of correlation between COD and selected water quality parameters in respect of Second order model

	Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
Y	1														
X1	- 0.7336	1													
X2	0.4101	-0.4011	1												
X3	- 0.4973	0.5623	-	1											
X4	0.6424	- 0.8532	0.5847	-	1										
X5	- 0.7335	1.0000	-	0.5618	-	1									
X6	0.4077	- 0.3975	1.0000	-	0.5815	-	1								
X7	- 0.5018	0.5689	-	1.0000	-	0.5685	-	1							
X8	0.6423	- 0.8529	0.5846	-	1.0000	-	0.5813	-	1						
X9	0.3098	- 0.4220	0.9851	-	0.5910	-	0.9850	-	0.5909	1					
X10	- 0.4835	0.5389	-	0.9995	-	0.5385	-	0.9992	-	-	1				
X11	0.6489	- 0.8835	0.6052	-	0.9933	-	0.6020	-	0.9932	0.6180	-	1			
X12	0.2240	- 0.1343	0.9427	-	0.2815	-	0.9440	-	0.2813	0.9242	-	0.3115	1		



Table 8: ANOVA of regression coefficient analysis of First Model

Source of Variation	Sum of Squares	Degree of freedom	Mean Sum of square	F-value	P-value
Between techniques	0.728295	1	0.728295	0.210928	0.66221
Within techniques	20.71683	6	3.452804		
Total	21.44512	7			

Table 9: ANOVA of regression coefficient analysis of Second Model

Source of Variation	Sum of Squares	Degree of freedom	Mean Sum of square	F-value	P-value
Between methods	289.40644	1	289.40644	1.9987623	0.1692902
Within methods	3764.6133	26	144.79282		
Total	4054.0198	27			

#### 4. Discussion

Groundwater constitutes an indispensable source of freshwater for drinking, domestic activities, and agricultural production in many rural and semi-urban communities across developing countries. In recent decades, however, the integrity and safety of these vital water resources have been increasingly compromised by anthropogenic activities, particularly mining. Mining operations can introduce a wide range of contaminants—including organic matter, suspended solids, heavy metals, and pathogenic microorganisms—into groundwater systems through leaching, runoff, and improper waste disposal. As a result, groundwater pollution associated with mining has emerged as a major global environmental concern, posing significant risks to public health, ecosystem stability, and sustainable water supply.

This study examines the interrelationships between Total Organic Carbon (TOC), colour, turbidity, microbial load, and Chemical

Oxygen Demand (COD) in groundwater affected by mining activities. The primary objective is to support rapid and reliable water-quality assessment, determine the level and nature of contamination, and provide a scientific basis for identifying appropriate and cost-effective treatment strategies. Groundwater samples were collected from wells and boreholes located in selected Local Government Areas of Osun State between July 2024 and May 2025. This sampling period and spatial coverage were deliberately chosen to capture variations in groundwater quality across different locations within the mining-impacted environment.

Comprehensive physicochemical and microbiological analyses were conducted on the collected groundwater samples. Empirical relationships between COD and selected water-quality parameters (TOC, colour, turbidity, and microbial load) were developed using both first-order and second-order regression models. Model solutions were

obtained using matrix functions in Microsoft Excel and independently validated using the Microsoft Excel Solver (MES) to ensure consistency, accuracy, and methodological robustness.

For the first-order model, regression coefficients for TOC, microbial load, colour, and turbidity were 2.7687, -0.0022, 4.5262, and 0.0831, respectively, using the matrix method, while corresponding coefficients of 2.8321, -0.0047, 2.0835, and 0.0559 were obtained using the MES technique. Statistical evaluation using analysis of variance (ANOVA) showed no significant difference between the coefficients generated by the two approaches at the 95% confidence level ( $F_{1,6} = 0.2109$ ,  $p = 0.6622$ ), confirming the reliability and equivalence of the modelling techniques. Similar trends and levels of agreement were observed for the second-order model, further reinforcing the consistency and applicability of the analytical approach.

Overall, the results demonstrate a strong correlation between TOC and COD, with TOC exhibiting high regression coefficients and strong predictive capability. This indicates that organic carbon plays a dominant role in driving oxygen demand in mining-contaminated groundwater. Moderate correlations between microbial load and colour suggest that microbial activity influences dissolved organic carbon and organic colour-causing materials in groundwater. In contrast, the weak correlation between turbidity and COD implies that suspended solids contribute only marginally to overall oxygen demand.

Additionally, the strong combined relationship among TOC, microbial load, and

COD suggests that elevated microbial activity may either enhance or inhibit organic oxidation processes within the groundwater system. Consequently, TOC can be reliably used as a surrogate parameter for estimating COD in mining-impacted groundwater.

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## 5 Recommendations

Based on the findings of this study, the following recommendations are proposed:

- a. The matrix-function modelling technique should be extended to more complex and nonlinear models to improve predictive accuracy.
- b. The applicability of the technique should be evaluated using additional water-quality models and other classes of pollutants beyond organic contamination.
- c. Data analysis capabilities in Microsoft Excel, particularly regression and modelling functions, should be enhanced through the use of add-ins, macros, or automation tools to improve efficiency and reproducibility.

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## 6 Conclusion

It can be concluded from this study that data-analysis functions in Microsoft Excel are effective for establishing reliable correlations among COD, TOC, colour, turbidity, and microbial load in groundwater systems. The strong correlation between TOC and COD confirms that organic carbon is a major driver of oxygen demand, implying that TOC and COD can, in many cases, be used interchangeably for groundwater quality assessment. The moderate correlations involving microbial load and colour indicate the influence of microbial processes on dissolved organic matter, while

the weak turbidity-COD relationship highlights the limited role of suspended solids in controlling COD. Overall, the study confirms that TOC is a reliable predictor of COD concentration in groundwater and provides a practical, cost-effective framework for rapid water-quality assessment and management in mining-impacted environments.

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#### REFERENCES

- Abdalla, K.Z. and Hammam, G. (2014). Correlation between biochemical oxygen demand and chemical oxygen demand for various wastewater treatment plants in Egypt to obtain the biodegradability indices, *International Journal of Sciences: Basic and Allied Research (IJSBAR)*, 13, 1, 42-48.
- Aguilar-Torrejón, J. A., Balderas-Hernández, P., Roa-Morales, G., Barrera-Díaz, C. E., Rodríguez-Torres, I., and Torres-Blancas, T. (2023). Relationship, importance, and development of analytical techniques: COD, BOD, and, Total Organic Carbon in water—An overview through time. *SN Allied Sciences*, 5(4), 118.
- Alewi, H. K., Abood, E. A., and Ali, G. (2022). An inquiry into the relationships between BOD<sub>5</sub>, COD, and TOTAL ORGANIC CARBON in Tigris River, Maysan Province, Iraq. *Caspian Journal of Environmental Sciences*, 20(1), 37-43.
- Anagnostopoulos, A.; Hjort, M.; Vaiopoulou, E. Assessment of Chemical Oxygen Demand/Total Organic Carbon (COD/Total Organic Carbon) ratios in

- refinery effluents. Report: Environmental Science for European Refining, no. 16/22. Brussels, 2022. Available online: [https://www.concawe.eu/publications/?\\_sft\\_topic=manufacturing-water-wastewater-emissions&\\_sft\\_publicationscategory=report](https://www.concawe.eu/publications/?_sft_topic=manufacturing-water-wastewater-emissions&_sft_publicationscategory=report) (accessed on 16 June 2025).
- APHA, (2019) Standard Method for the Examination of Water and Wastewater, 24<sup>th</sup> edn, America Water Works Association and Water Pollution Control Federation, Washington DC
- Assefa, E., Jabasingh, A., Mulugeta, E., Dessalegne, M., & Teju, E. (2024). Impact of source water quality on total organic carbon and trihalomethane removal efficiency in a water treatment plant: A case study of Upper Awash, Ethiopia. *Journal of Water and Health*, 22(2), 337-349.
- Baker, J. R., Milke, M. W., and Mihelcic, J. R. (1999). Relationship between chemical and theoretical oxygen demand for specific classes of organic chemicals. *Water*
- Bhat, M.R., Hiremath, R.S. and Kulkarni, V.R. (2003). Correlation between BOD, COD and TOTAL ORGANIC CARBON, *Journal of Industrial Pollution Control*, 19,2, . 187-191.
- Christian, E., Batista, J. R., and Gerrity, D. (2017). Use of COD, TOTAL ORGANIC CARBON, and fluorescence spectroscopy to estimate BOD in wastewater. *Water Environment Research*, 89(2), 168-177.
- Cossu, R., Lai, T. and Sandon, A. (2012). Standardization of BOD<sub>5</sub>/COD ratio as a biological stability index for MSW, *Waste Management*, (32), . 1503-1508.
- Costa, S. P., Cunha, E., Azevedo, A. M., Pereira, S. A., Neves, A. F., Vilar, A. G. & Saraiva, M. L. (2018) Microfluidic chemiluminescence system with yeast *Saccharomyces cerevisiae* for rapid biochemical oxygen demand measurement. *ACSSustainable Chemistry and Engineering* 6(5), 6094-6101. <https://doi.org/10.1021/acssuschemeng.7b04736>.
- Crini, G., Lacalamita, D., Lichtfouse, E., Morin-Crini, N., Liu, C., Wilson, L. D., ... and Mongioví, C. (2024). Characterization and treatment of industrial laundry wastewaters: a review. *Environmental Chemistry Letters*, 22(5), 2257-2292.
- Doaemo, W., Betasolo, M., Montenegro, J. F., Pizzigoni, S., Kvashuk, A., Femeena, P. V., and Mohan, M. (2023). Evaluating the Impacts of Environmental and Anthropogenic Factors on Water Quality in the Bumbu River Watershed, Papua New Guinea. *Water*, 15(3), 489.
- El Mourabit, Y., Assabbane, A., and Hamdani, M. (2020). Study of correlations between microbiological and physicochemical parameters of drinking water quality in El kolea city (Agadir, Morocco): Using multivariate statistical methods. *J. Mater. Environ. Sci*, 11, 310-317.
- El Mourabit, Y., Assabbane, A., and Hamdani, M. (2020). Study of correlations between microbiological and physicochemical parameters of drinking water quality in El kolea city (Agadir, Morocco): Using multivariate statistical methods. *J. Mater. Environ. Sci*, 11, 310-317.
- Elgalabwater (2025) Sources of Total Organic Carbon in water. [https://www.elgalabwater.com/blog/total-organic-carbon-toc?utm\\_source=chatgpt.com](https://www.elgalabwater.com/blog/total-organic-carbon-toc?utm_source=chatgpt.com)
- Etisa, D., Kifle, D., and Fetahi, T. (2024). Phytoplankton functional dynamics in relation to some physicochemical parameters in Lake Kuriftu (Oromia, Ethiopia). *Algal Research*, 79, 103462.

- Geerdink RB, Sebastiaan van den Hurk R, Epema OJ.(2017). Chemical oxygen demand: Historical perspectives and future challenges. *Anal Chim Acta*. 2017 Apr 8;961:1-11. doi: 10.1016/j.aca.2017.01.009. Epub 2017 Jan 24. PMID: 28224900.
- Gong, C., Zhang, H., Huo, S., Zhang, J., Weng, N., and Li, W. (2025). Transformation processes of total suspended solids and dissolved organic matter in rivers: Influences of different land use sources and degradation processes. *Science of The Total Environment*, 963, 178509.
- Gu, Q., Wang, K., Li, J., Ma, L., Deng, J., Zheng, K., and Sheng, L. (2015). Spatio-temporal trends and identification of correlated variables with water quality for drinking-water reservoirs. *International Journal of Environmental Research and Public Health*, 12(10), 13179-13194.
- Hartz L, Grabinski L and Salameh S (2025) Microplastic pollution in aquatic environments: a meta-analysis of influencing factors and methodological recommendations. *Front. Environ. Sci.* 13:1600570. doi: 10.3389/fenvs.2025.1600570
- Hassan, A., Ilyas, S. Z., Jalil, A., and Ullah, Z. (2021). Monetization of the environmental damage caused by fossil fuels. *Environmental Science and Pollution Research*, 28, 21204-21211.
- Health Canada (2020). *Guidance on Natural Organic Matter in Drinking Water*. Water and Air Quality Bureau, Healthy Environments and Consumer Safety Branch, Health Canada, Ottawa, Ontario. (Catalogue No. H144-67/2020E-PDF). [https://www.printfriendly.com/print/?source=cs&url=https%3A%2F%2Fmantech-inc.com%2Fblog%2Fguidance-on-natural-organic-matter-in-drinking-water-adds-cod-parameter-references-pecod-method%2F%3Futm\\_source%3Dchatgpt.com&headerImageUrl=&headerTagline=&imageDisplayStyle=left&disableClickToDel=0&disablePDF=0&encodeImages=false&showHiddenContent=false&disablePrint=0&disableEmail=0&imagesSize=full-size&fallbackStrategy=algo&primaryImage=all&fetchOriginalPage=default](https://www.printfriendly.com/print/?source=cs&url=https%3A%2F%2Fmantech-inc.com%2Fblog%2Fguidance-on-natural-organic-matter-in-drinking-water-adds-cod-parameter-references-pecod-method%2F%3Futm_source%3Dchatgpt.com&headerImageUrl=&headerTagline=&imageDisplayStyle=left&disableClickToDel=0&disablePDF=0&encodeImages=false&showHiddenContent=false&disablePrint=0&disableEmail=0&imagesSize=full-size&fallbackStrategy=algo&primaryImage=all&fetchOriginalPage=default)
- Hocaoglu, S.M. and Orhon, D. (2013). Particle size distribution analysis of chemical oxygen demand fractions with different biodegradation characteristics in black water and gray water, *Clean - Soil, Air, Water*, 41, 11, . 1044-1051
- Hsiang, S., Oliva, P., and Walker, R. (2019). The distribution of environmental damages. *Review of Environmental Economics and Policy*.
- Jiao, N., Liu, J., Edwards, B., Lv, Z., Cai, R., Liu, Y., and Legendre, L. (2021). Correcting a major error in assessing organic carbon pollution in natural waters. *Science Advances*, 7(16), eabc7318.
- Jin, P., Wang, Bi., Jiao, D., Sun, G., Wang, Ba. and Wang, X.C. (2015). Characterization of microflora and transformation of organic matters in urban sewer system, *Water Research*, 84, . 112-119
- Jouanneau S, Recoules L, Durand MJ, Boukabache A, Picot V, Primault Y, Lakel A, Sengelin M, Barillon B, Thouand G.(2013). Methods for assessing biochemical oxygen demand (BOD): a review. *Water Res.* 2014 Feb 1;49:62-82. doi: 10.1016/j.watres.2013.10.066. Epub 2013 Nov 12. PMID: 24316182.
- Kafle, B.P (2019). *Chemical Analysis and Material Characterization by Spectrophotometry*. Elsevier Radarweg 29, 1000 AE Amsterdam,

- Kang, D. H., So, Y. H., Park, K. D., Kim, I. K., and Kim, B. W. (2019). Analyses of TOTAL ORGANIC CARBON efficiency and correlation between DO, BOD, COD and influence factors using long-term observation data in the main stream of Nakdong River. *Journal of Environmental Science International*, 28(5), 465-474.
- Kim, J. H., and Jo, J. (2016). Chemical oxygen demand (COD) model for the assessment of water quality in the Han River, Korea. *Journal of Environmental Health Sciences*, 42(4), 280-292.
- Kumar, D., Kumar, R., Sharma, M., Awasthi, A., and Kumar, M. (2024). Global water quality indices: Development, implications, and limitations. *Total Environment Advances*, 9, 200095.
- Kuznietsov, P. M., and Biedunkova, O. O. (2024b). Multivariate regression studies for the investigation of the COD, BOD, and TOTAL ORGANIC CARBON concentrations in the water of the Styr River within the zone of influence of the power plant discharge. *Water Practice and Technology*, 19(4), 1412-1426.
- Kuznietsov, P. M., Biedunkova, O. O., Yaroshchuk, O. V. & Pryshchepa, A. M. (2024) Optimization of the anti-scale corrective treatment of water by organic phosphonate. *Science and Innovation* 20(2),79-90.<https://doi.org/10.15407/scine20.02.079>.
- Kuznietsov, P., and Biedunkova, O. (2024a). Assessment of the impact of organic matter discharge from a nuclear power plant with a recirculating cooling water system. *Water, Air, and Soil Pollution*, 235(4), 221.
- Lacalamita, D., Mongioví, C., and Crini, G. (2024). Chemical oxygen demand and biochemical oxygen demand analysis of discharge waters from laundry industry: monitoring, temporal variability, and biodegradability. *Frontiers in Environmental Science*, 12, 1387041.
- Lee, A.H. and Nikraz, H. (2014). BOD:COD ratio as an indicator for pollutants leaching from landfill, *Journal of Clean Energy Technology*, 2, 3, . 263-266.
- Lee, A.H. and Nikraz, H. (2015). BOD:COD ratio as an indicator for river pollution, *International Proceedings of Chemical, Biological and Environmental Engineering*, 88, 15, . 89-94.
- Li J, Luo G, He L, Xu J, Lyu J. (2018). Analytical Approaches for Determining Chemical Oxygen Demand in Water Bodies: A Review. *Crit Rev Anal Chem*. Jan 2;48(1):47-65. doi: 10.1080/10408347.2017.1370670. Epub 2017 Oct 30. PMID: 28857621.
- Liu, D., Jiang, X., Duan, M., Yu, S., and Bai, Y. (2023). Human and natural activities regulate organic matter transport in Chinese rivers. *Water Research*, 245, 120622.
- Liu, D., Tian, L., Jiang, X., Wu, H., and Yu, S. (2022). Human activities changed organic carbon transport in Chinese rivers during 2004-2018. *Water Research*, 222, 118872.
- Lopes, J., Pinto, A. S., Eleutério, T., Meirelles, M. G., and Vasconcelos, H. C. (2022). Multivariate Statistical Analysis of the Phytoplankton Interactions with Physicochemical and Meteorological Parameters in Volcanic Crater Lakes from Azores. *Water*, 14(16), 2548.
- Makumbura, R. K., Mampitiya, L., Rathnayake, N., Meddage, D. P. P., Henna, S., Dang, T. L., and Rathnayake, U. (2024). Advancing water quality assessment and prediction using machine learning models, coupled with explainable artificial intelligence

- (XAI) techniques like shapley additive explanations (SHAP) for interpreting the black-box nature. *Results in Engineering*, 23, 102831.
- Mamun, M., Kim, J. Y., Kim, J. E., and An, K. G. (2022). Longitudinal chemical gradients and the functional responses of nutrients, organic matter, and other parameters to the land use pattern and monsoon intensity. *Water*, 14(2), 237.
- Nuraya, T., & Agawaman, L. P. I. (2025). Effect of River Organic Carbon Input in Mangrove Sediment. *Jurnal Penelitian Pendidikan IPA*, 11(2), 1043-1052.
- Pervin, T., Gerdtham, U. G., & Lyttkens, C. H. (2008). Societal costs of air pollution-related health hazards: A review of methods and results. *Cost Effectiveness and Resource Allocation*, 6, 1-22.
- Recoules, L., Jouanneau, S., Thouand, G., Gue, A. M & Boukabache, A. 2019 Towards a miniaturized device to evaluate the BOD parameter of wastewater. *International Journal of Environmental Science and Development* 10(6), 178-182. <https://doi.org/10.18178/ijesd.2019.10.6.1168>.
- Sáez-Ardura, F., Parra-Salazar, M., Vallejos-Romero, A., Rodríguez-Rodríguez, I., Cordoves-Sánchez, M., Cisternas-Irarrázabal, C., and Genaro, V. (2025). Exploring the Socio-Environmental Regulation of Water—A Systematic Review of Sustainable Watershed Management. *Sustainability*, 17(4), 1588.
- Scholes, E., Verheyen, V. and Brook-Carter, P. (2016). A review of practical tools for rapid monitoring of membrane bioreactors, *Water Research*, 102, . 252-262.
- Senoro, D. B., De Jesus, K. L. M., and Monjardin, C. E. F. (2023). Pollution and Risk Evaluation of Toxic Metals and Metalloid in Water Resources of San Jose, Occidental Mindoro, Philippines. *Sustainability*, 15(4), 3667.
- Si, H., Pan, N., Zhang, X., Liao, J., Romyantseva, M. N., Gaskov, A. M. & Lin, S. 2019 A real-time on-line photoelectrochemical sensor toward chemical oxygen demand determination based on field-effect transistor using an extended gate with 3D TiO<sub>2</sub> nanotube arrays. *Sensors and Actuators. B: Chemical* 289, 106-113. <https://doi.org/10.1016/j.snb.2019.03.071>.
- Siwec, T., Kiedryńska, L., Abramowicz, K. and Rewicka, A. (2012). Analysis of chosen models describing the changes in BOD<sub>5</sub> in sewages, *Environment Protection Engineering*, (38), 2, . 61-76.
- Siwec, T., Reczek, L., Michel, M. M., Gut, B., Haver-Strojek, P., Czajkowska, J., and Bugajski, P. (2018). Correlations between organic pollution indicators in municipal wastewater. *Archives of Environmental Protection*, 44(4).
- Sodikin, W., Juwono, P. T., & Sholichin, M. (2025). Assessment of Baseflow Characteristics and Environmental Flow Allocation in the Welo Sub-Watershed, Central Java. *Jurnal Penelitian Pendidikan IPA*, 11(4), 672-684
- Szaja, A., Aguilar, J.A. and Łagód, G. (2015). Estimation of chemical oxygen demand fractions of municipal wastewater by respirometric method - case study, *Annual Set Environmental Protection*, 17, . 289-299.
- Tomczyk, P., Tymcio, M., Kuriqi, A., Santos, J. M., and Wiatkowski, M. (2025). Small hydropower impacts on water quality: a comparative analysis of different assessment methods. *Water Resources and Industry*, 100282.

- Ukaogo, P. O., Ewuzie, U., and Onwuka, C. V. (2020). Environmental pollution: causes, effects, and the remedies. In *Microorganisms for sustainable environment and health* (. 419-429). Elsevier.
- Van Loosdrecht, M.C.M., Nielsen, P.H., Lopez-Vazquez, C.M., Brdjanovic, D., (2016). *Experimental Methods in Wastewater Treatment*. 1st Edition, International Water Publishing Alliance House, London
- Wang H, Yu S, Sun L, Wang Y, Wu H and Wang X (2025) Pollution assessment and health risk of metals in surface soil near a Pb-Zn mine, northeast China. *Front. Environ. Sci.* 13:1585272. doi: 10.3389/fenvs.2025.1585272.
- Wojnárovits, L., Homlok, R., Kovács, K., Tegze, A., and Takács, E. (2024). Wastewater characterization: chemical oxygen demand or total organic carbon content measurement?. *Molecules*, 29(2), 405
- Wu, D., Hu, Y. & Liu, Y. (2022). A Review of Detection Techniques for Chemical Oxygen Demand in Wastewater. *American Journal of Biochemistry and Biotechnology*, 18(1), 23-32. <https://doi.org/10.3844/ajbbbsp.2022.23.32>
- Zak, D., Hupfer, M., Cabezas, A., Jurasinski, G., Audet, J., Kleeberg, A., McInnes, R., Kristiansen, S. M., Petersen, R. J., Liu, H. & Goldhammer, T. 2021 Sulphate in freshwater ecosystems: A review of sources, biogeochemical cycles, ecotoxicological effects and bioremediation. *Earth-Science Reviews* 212, 243-256. <https://doi.org/10.1016/j.earscirev.2020.103446>.
- Zuo, K., Garcia-Segura, S., Cerrón-Calle, G. A., Chen, F. Y., Tian, X., Wang, X., and Li, Q. (2023). Electrified water treatment: fundamentals and roles of electrode materials. *Nature Reviews Materials*, 8(7), 472-490.

### Appendix A: Least Square equations of the models

First order model least square equations

$$Y = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4$$

Least Square transformation

$$\sum_{i=1}^N Y = \alpha_1 \sum_{i=1}^N X_1 + \alpha_2 \sum_{i=1}^N X_2 + ..$$

$$\alpha_3 \sum_{i=1}^N X_3 + \alpha_4 \sum_{i=1}^N X_4$$

a1

$$\sum_{i=1}^N X_3 Y = \alpha_1 \sum_{i=1}^N X_3 X_1 + ..$$

$$\alpha_2 \sum_{i=1}^N X_3 X_2 + \alpha_3 \sum_{i=1}^N X_3 X_3 + ..$$

a4

$$\alpha_4 \sum_{i=1}^N X_3 X_4$$

Second-order model least square equations

$$\sum_{i=1}^N X_1 Y = \alpha_1 \sum_{i=1}^N X_1 X_1 + ..$$

$$\alpha_2 \sum_{i=1}^N X_1 X_2 + \alpha_3 \sum_{i=1}^N X_1 X_3 ..$$

a2

$$+ \alpha_4 \sum_{i=1}^N X_1 X_4$$

$$\sum_{i=1}^N X_2 Y = \alpha_1 \sum_{i=1}^N X_2 X_1 + ..$$

$$\alpha_2 \sum_{i=1}^N X_2 X_2 + \alpha_3 \sum_{i=1}^N X_2 X_3 ..$$

a3

$$+ \alpha_4 \sum_{i=1}^N X_2 X_4$$

$$Y = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 ..$$

$$+ \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + ..$$

$$... \alpha_7 X_7 + \alpha_8 X_8 + \alpha_9 X_9 .....$$

(1)

$$+ \alpha_{10} X_{10} + \alpha_{11} X_{11} + \alpha_{12} X_{12} ..$$

$$+ \alpha_{13} X_{13} + \alpha_{14} X_{14}$$

Where; Y is the COD; X<sub>1</sub> is the Total Organic Carbon, Microbial load (CFU/100 ml), X<sub>3</sub> is the Colour, X<sub>4</sub> is the Turbidity, X<sub>5</sub> is the Total Organic Carbon and Total Organic Carbon, X<sub>6</sub> is the Total Organic Carbon and Microbial load (CFU/100 ml), X<sub>7</sub> is the Total Organic Carbon and Colour, X<sub>8</sub> is the Total Organic Carbon and Turbidity, X<sub>9</sub> is the Microbial Load (Cfu/100 ML) and Microbial load (CFU/100 ml), X<sub>10</sub> is the Colour and Colour, X<sub>11</sub> is the Turbidity and Turbidity, X<sub>12</sub> is the Microbial Load (CFU/100 ML), and Colour, X<sub>13</sub> is the Microbial Load (CFU/100 ML), and Turbidity, and X<sub>14</sub> is the Colour and Turbidity.

### Least Squares transformation

$$\sum_{i=1}^N Y_i = \alpha_1 \sum_{i=1}^N X_1 + \alpha_2 \sum_{i=1}^N X_2 ..$$

$$+ \alpha_3 \sum_{i=1}^N X_3 + \alpha_4 \sum_{i=1}^N X_4 + \alpha_5 \sum_{i=1}^N X_5 ..$$

$$+ \alpha_6 \sum_{i=1}^N X_6 + \alpha_7 \sum_{i=1}^N X_7 + \alpha_8 \sum_{i=1}^N X_8 ..$$

$$+ \alpha_9 \sum_{i=1}^N X_9 + \alpha_{10} \sum_{i=1}^N X_{10} + \alpha_{11} \sum_{i=1}^N X_{11} ..$$

$$+ \alpha_{12} \sum_{i=1}^N X_{12} + \alpha_{13} \sum_{i=1}^N X_{13} + \alpha_{14} \sum_{i=1}^N X_{14}$$

(1)

$$\sum_{i=1}^N Y_i X_1 = \alpha_1 \sum_{i=1}^N X_1 X_1 + \alpha_2 \sum_{i=1}^N X_1 X_2 ..$$

$$+ \alpha_3 \sum_{i=1}^N X_1 X_3 + \alpha_4 \sum_{i=1}^N X_1 X_4 + \alpha_5 \sum_{i=1}^N X_1 X_5 ..$$

$$+ \alpha_6 \sum_{i=1}^N X_1 X_6 + \alpha_7 \sum_{i=1}^N X_1 X_7 + \alpha_8 \sum_{i=1}^N X_1 X_8 ..$$

$$+ \alpha_9 \sum_{i=1}^N X_1 X_9 + \alpha_{10} \sum_{i=1}^N X_1 X_{10} + \alpha_{11} \sum_{i=1}^N X_1 X_{11} ..$$

$$+ \alpha_{12} \sum_{i=1}^N X_1 X_{12} + \alpha_{13} \sum_{i=1}^N X_1 X_{13} + \alpha_{14} \sum_{i=1}^N X_1 X_{14}$$

(2)

$$\begin{aligned}
\sum_{i=1}^N X_2 Y_i &= \alpha_1 \sum_{i=1}^N X_2 X_1 + \alpha_2 \sum_{i=1}^N X_2 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_2 X_3 + \alpha_4 \sum_{i=1}^N X_2 X_4 + \alpha_5 \sum_{i=1}^N X_2 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_2 X_6 + \alpha_7 \sum_{i=1}^N X_2 X_7 + \alpha_8 \sum_{i=1}^N X_2 X_8 \dots \quad (3) \\
&+ \alpha_9 \sum_{i=1}^N X_2 X_9 + \alpha_{10} \sum_{i=1}^N X_2 X_{10} + \alpha_{11} \sum_{i=1}^N X_2 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_2 X_{12} + \alpha_{13} \sum_{i=1}^N X_2 X_{13} + \alpha_{14} \sum_{i=1}^N X_2 X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_3 Y_i &= \alpha_1 \sum_{i=1}^N X_3 X_1 + \alpha_2 \sum_{i=1}^N X_3 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_3 X_3 + \alpha_4 \sum_{i=1}^N X_3 X_4 + \alpha_5 \sum_{i=1}^N X_3 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_3 X_6 + \alpha_7 \sum_{i=1}^N X_3 X_7 + \alpha_8 \sum_{i=1}^N X_3 X_8 \dots \\
&+ \alpha_9 \sum_{i=1}^N X_3 X_9 + \alpha_{10} \sum_{i=1}^N X_3 X_{10} + \alpha_{11} \sum_{i=1}^N X_3 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_3 X_{12} + \alpha_{13} \sum_{i=1}^N X_3 X_{13} + \alpha_{14} \sum_{i=1}^N X_3 X_{14}
\end{aligned} \quad (6)$$

$$\begin{aligned}
\sum_{i=1}^N X_3 Y_i &= \alpha_1 \sum_{i=1}^N X_3 X_1 + \alpha_2 \sum_{i=1}^N X_3 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_3 X_3 + \alpha_4 \sum_{i=1}^N X_3 X_4 + \alpha_5 \sum_{i=1}^N X_3 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_3 X_6 + \alpha_7 \sum_{i=1}^N X_3 X_7 + \alpha_8 \sum_{i=1}^N X_3 X_8 \dots \quad (4) \\
&+ \alpha_9 \sum_{i=1}^N X_3 X_9 + \alpha_{10} \sum_{i=1}^N X_3 X_{10} + \alpha_{11} \sum_{i=1}^N X_3 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_3 X_{12} + \alpha_{13} \sum_{i=1}^N X_3 X_{13} + \alpha_{14} \sum_{i=1}^N X_3 X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_6 Y_i &= \alpha_1 \sum_{i=1}^N X_6 X_1 + \alpha_2 \sum_{i=1}^N X_6 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_6 X_3 + \alpha_4 \sum_{i=1}^N X_6 X_4 + \alpha_5 \sum_{i=1}^N X_6 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_6 X_6 + \alpha_7 \sum_{i=1}^N X_6 X_7 + \alpha_8 \sum_{i=1}^N X_6 X_8 \dots \\
&+ \alpha_9 \sum_{i=1}^N X_6 X_9 + \alpha_{10} \sum_{i=1}^N X_6 X_{10} + \alpha_{11} \sum_{i=1}^N X_6 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_6 X_{12} + \alpha_{13} \sum_{i=1}^N X_6 X_{13} + \alpha_{14} \sum_{i=1}^N X_6 X_{14}
\end{aligned} \quad (7)$$

$$\begin{aligned}
\sum_{i=1}^N X_4 Y_i &= \alpha_1 \sum_{i=1}^N X_4 X_1 + \alpha_2 \sum_{i=1}^N X_4 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_4 X_3 + \alpha_4 \sum_{i=1}^N X_4 X_4 + \alpha_5 \sum_{i=1}^N X_4 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_4 X_6 + \alpha_7 \sum_{i=1}^N X_4 X_7 + \alpha_8 \sum_{i=1}^N X_4 X_8 \dots \quad (5) \\
&+ \alpha_9 \sum_{i=1}^N X_4 X_9 + \alpha_{10} \sum_{i=1}^N X_4 X_{10} + \alpha_{11} \sum_{i=1}^N X_4 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_4 X_{12} + \alpha_{13} \sum_{i=1}^N X_4 X_{13} + \alpha_{14} \sum_{i=1}^N X_4 X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_7 Y_i &= \alpha_1 \sum_{i=1}^N X_7 X_1 + \alpha_2 \sum_{i=1}^N X_7 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_7 X_3 + \alpha_4 \sum_{i=1}^N X_7 X_4 + \alpha_5 \sum_{i=1}^N X_7 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_7 X_6 + \alpha_7 \sum_{i=1}^N X_7 X_7 + \alpha_8 \sum_{i=1}^N X_7 X_8 \dots \\
&+ \alpha_9 \sum_{i=1}^N X_7 X_9 + \alpha_{10} \sum_{i=1}^N X_7 X_{10} + \alpha_{11} \sum_{i=1}^N X_7 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_7 X_{12} + \alpha_{13} \sum_{i=1}^N X_7 X_{13} + \alpha_{14} \sum_{i=1}^N X_7 X_{14}
\end{aligned} \quad (8)$$

$$\begin{aligned}
\sum_{i=1}^N X_8 Y_i &= \alpha_1 \sum_{i=1}^N X_8 X_1 + \alpha_2 \sum_{i=1}^N X_8 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_8 X_3 + \alpha_4 \sum_{i=1}^N X_8 X_4 + \alpha_5 \sum_{i=1}^N X_8 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_8 X_6 + \alpha_7 \sum_{i=1}^N X_8 X_7 + \alpha_8 \sum_{i=1}^N X_8 X_8 \dots \quad (9) \\
&+ \alpha_9 \sum_{i=1}^N X_8 X_9 + \alpha_{10} \sum_{i=1}^N X_8 X_{10} + \alpha_{11} \sum_{i=1}^N X_8 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_8 X_{12} + \alpha_{13} \sum_{i=1}^N X_8 X_{13} + \alpha_{14} \sum_{i=1}^N X_8 X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_{10} Y_i &= \alpha_1 \sum_{i=1}^N X_{10} X_1 + \alpha_2 \sum_{i=1}^N X_{10} X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_{10} X_3 + \alpha_4 \sum_{i=1}^N X_{10} X_4 + \alpha_5 \sum_{i=1}^N X_{10} X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_{10} X_6 + \alpha_7 \sum_{i=1}^N X_{10} X_7 + \alpha_8 \sum_{i=1}^N X_{10} X_8 \dots \quad (11) \\
&+ \alpha_9 \sum_{i=1}^N X_{10} X_9 + \alpha_{10} \sum_{i=1}^N X_{10} X_{10} + \alpha_{11} \sum_{i=1}^N X_{10} X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_{10} X_{12} + \alpha_{13} \sum_{i=1}^N X_{10} X_{13} + \alpha_{14} \sum_{i=1}^N X_{10} X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_9 Y_i &= \alpha_1 \sum_{i=1}^N X_9 X_1 + \alpha_2 \sum_{i=1}^N X_9 X_2 \dots \\
&+ \alpha_3 \sum_{i=1}^N X_9 X_3 + \alpha_4 \sum_{i=1}^N X_9 X_4 + \alpha_5 \sum_{i=1}^N X_9 X_5 \dots \\
&+ \alpha_6 \sum_{i=1}^N X_9 X_6 + \alpha_7 \sum_{i=1}^N X_9 X_7 + \alpha_8 \sum_{i=1}^N X_9 X_8 \dots \quad (10) \\
&+ \alpha_9 \sum_{i=1}^N X_9 X_9 + \alpha_{10} \sum_{i=1}^N X_9 X_{10} + \alpha_{11} \sum_{i=1}^N X_9 X_{11} \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_9 X_{12} + \alpha_{13} \sum_{i=1}^N X_9 X_{13} + \alpha_{14} \sum_{i=1}^N X_9 X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_{11} Y_i &= \alpha_1 \sum_{i=1}^N X_{11} X_1 + \alpha_2 \sum_{i=1}^N X_{11} X_2 + \dots \\
&+ \alpha_3 \sum_{i=1}^N X_{11} X_3 + \alpha_4 \sum_{i=1}^N X_{11} X_4 + \alpha_5 \sum_{i=1}^N X_{11} X_5 + \dots \\
&+ \alpha_6 \sum_{i=1}^N X_{11} X_6 + \alpha_7 \sum_{i=1}^N X_{11} X_7 + \alpha_8 \sum_{i=1}^N X_{11} X_8 + \dots \\
&+ \alpha_9 \sum_{i=1}^N X_{11} X_9 + \alpha_{10} \sum_{i=1}^N X_{11} X_{10} + \alpha_{11} \sum_{i=1}^N X_{11} X_{11} + \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_{11} X_{12} + \alpha_{13} \sum_{i=1}^N X_{11} X_{13} + \alpha_{14} \sum_{i=1}^N X_{11} X_{14}
\end{aligned}$$

12)

$$\begin{aligned}
\sum_{i=1}^N X_{12} Y_i &= \alpha_1 \sum_{i=1}^N X_{12} X_1 + \alpha_2 \sum_{i=1}^N X_{12} X_2 + \dots \\
&+ \alpha_3 \sum_{i=1}^N X_{12} X_3 + \alpha_4 \sum_{i=1}^N X_{12} X_4 + \alpha_5 \sum_{i=1}^N X_{12} X_5 + \dots \\
&+ \alpha_6 \sum_{i=1}^N X_{12} X_6 + \alpha_7 \sum_{i=1}^N X_{12} X_7 + \alpha_8 \sum_{i=1}^N X_{12} X_8 + \dots \quad (13) \\
&+ \alpha_9 \sum_{i=1}^N X_{12} X_9 + \alpha_{10} \sum_{i=1}^N X_{12} X_{10} + \alpha_{11} \sum_{i=1}^N X_{12} X_{11} + \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_{12} X_{12} + \alpha_{13} \sum_{i=1}^N X_{12} X_{13} + \alpha_{14} \sum_{i=1}^N X_{12} X_{14}
\end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^N X_{13} Y_i &= \alpha_1 \sum_{i=1}^N X_{13} X_1 + \alpha_2 \sum_{i=1}^N X_{13} X_2 + \dots \\
&+ \alpha_3 \sum_{i=1}^N X_{13} X_3 + \alpha_4 \sum_{i=1}^N X_{13} X_4 + \alpha_5 \sum_{i=1}^N X_{13} X_5 + \dots \\
&+ \alpha_6 \sum_{i=1}^N X_{13} X_6 + \alpha_7 \sum_{i=1}^N X_{13} X_7 + \alpha_8 \sum_{i=1}^N X_{13} X_8 + \dots \quad (14) \\
&+ \alpha_9 \sum_{i=1}^N X_{13} X_9 + \alpha_{10} \sum_{i=1}^N X_{13} X_{10} + \alpha_{11} \sum_{i=1}^N X_{13} X_{11} + \dots \\
&+ \alpha_{12} \sum_{i=1}^N X_{13} X_{12} + \alpha_{13} \sum_{i=1}^N X_{13} X_{13} + \alpha_{14} \sum_{i=1}^N X_{13} X_{14}
\end{aligned}$$

**Appendix B: Matrices of the models**  
**Second order model matrix**

Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
2.99E+03	1.82E+02	2.88E+03	2.20E+01	2.74E+02	3.00E+04	1.73E+05	7.40E+02	1.74E+03	2.17E+06	8.32E+07
9.03E+04	3.00E+04	1.73E+05	7.40E+02	1.74E+03	5.20E+06	2.94E+07	1.23E+05	2.23E+05	1.68E+08	3.01E+09
1.44E+06	1.73E+05	2.17E+06	1.01E+04	2.25E+05	2.94E+07	1.68E+08	7.05E+05	1.63E+06	1.94E+09	3.67E+10
1.10E+04	7.40E+02	1.01E+04	8.32E+01	7.84E+02	1.23E+05	5.04E+06	3.01E+03	6.55E+03	7.43E+06	3.20E+07
1.38E+05	1.74E+03	2.25E+05	7.84E+02	4.48E+04	2.23E+05	1.63E+06	6.55E+03	8.67E+04	2.08E+08	2.30E+09
1.49E+07	5.20E+06	2.94E+07	1.23E+05	2.23E+05	9.01E+08	5.10E+09	2.13E+07	3.85E+07	2.88E+10	5.02E+11
8.59E+07	2.94E+07	1.68E+08	7.05E+05	1.63E+06	5.10E+09	2.88E+10	1.20E+08	2.19E+08	1.65E+11	2.88E+12
3.67E+05	1.23E+05	7.05E+05	3.01E+03	6.55E+03	2.13E+07	1.20E+08	5.02E+05	9.12E+05	6.87E+08	1.23E+09
8.68E+05	2.23E+05	1.63E+06	6.55E+03	8.67E+04	3.85E+07	2.19E+08	9.12E+05	1.78E+06	1.58E+09	2.52E+10
1.08E+09	1.68E+08	1.94E+09	7.43E+06	2.08E+08	2.88E+10	1.65E+11	6.87E+08	1.58E+09	1.84E+12	2.65E+13
4.14E+04	3.01E+03	3.67E+04	3.20E+02	2.30E+03	5.02E+05	2.88E+06	1.23E+04	2.52E+04	2.65E+07	1.84E+08
2.26E+07	8.67E+04	4.26E+07	1.20E+05	9.06E+06	1.78E+06	8.26E+07	2.45E+05	1.57E+07	4.12E+10	3.20E+11
5.04E+06	7.05E+05	7.43E+06	3.67E+04	6.18E+05	1.20E+08	6.87E+08	2.88E+06	6.16E+05	6.58E+09	1.37E+10
1.13E+08	1.63E+06	2.08E+08	6.18E+05	4.26E+07	2.19E+08	1.58E+09	6.16E+06	1.78E+06	2.00E+11	1.72E+12

**Inverse of Second order model Matrix**

Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
2.99 E+03	-3.72E+02	3.55E+02	1.73E-01	-8.34E-07	-2.37E+01	-1.83E+00	3.96E-07	-3.00E+01	1.18E+01	3.14E-06
9.03E+04	6.40E+01	-1.61E+01	5.78E-02	-1.10E-06	-4.45E+01	-8.86E-01	2.59E-07	-3.94E+00	2.53E+01	5.30E-06
1.44E+06	1.01E+02	-1.55E+02	9.62E-02	1.19E-06	-2.00E+02	-4.61E+00	1.48E-06	2.48E+01	1.16E+02	-9.03E-06
1.10E+04	-1.62E+02	3.58E+01	-1.64E-01	6.36E-07	1.18E+02	2.37E+00	-1.59E-07	1.10E+01	-6.69E+01	3.76E-07
1.38E+05	-2.60E+00	-1.23E+00	-2.25E-03	-1.28E-06	1.82E-01	-4.19E-03	-1.98E-09	6.09E-01	-7.14E-02	-2.26E-08
1.49E+07	-1.09E-06	-7.68E-08	-5.35E-10	2.31E-07	-9.72E-08	-2.89E-09	1.06E-15	2.58E-08	6.45E-08	-1.11E-14
8.59E+07	2.02E+02	-3.41E+01	6.04E-02	-2.68E-07	-1.98E+00	6.26E-01	-1.20E-08	-1.87E+01	1.50E-01	2.00E-07
3.67E+05	1.40E-05	1.18E-06	7.83E-07	1.83E-14	3.06E-07	5.44E-08	-4.15E-15	4.52E-08	-1.47E-06	-4.41E-14
8.68E+05	-2.70E-04	-9.78E-06	-6.94E-06	-1.57E-13	3.97E-06	-7.10E-07	6.11E-14	-4.70E-07	1.84E-05	3.45E-13
1.08E+09	8.85E-10	-4.89E-10	-2.21E-11	-7.51E-15	-3.20E-10	-1.16E-11	9.75E-19	1.52E-10	2.14E-10	8.64E-14
4.14E+04	5.17E-03	-2.82E-03	-1.27E-04	-4.33E-08	-1.85E-03	-6.71E-05	5.61E-12	8.77E-04	1.23E-03	4.99E-07
2.26E+07	-1.57E+01	3.96E+00	-1.37E-02	1.52E-07	1.10E+01	2.18E-01	-6.36E-08	9.71E-01	-6.23E+00	-1.08E-06
5.04E+06	5.67E-02	-9.25E-03	1.22E-04	1.00E-08	-4.37E-02	-8.82E-04	1.99E-10	-4.58E-03	2.47E-02	-1.19E-07
1.13E+08	-2.42E-05	-7.13E-07	-1.61E-07	-5.40E-14	-9.54E-08	9.44E-07	-1.80E-07	3.38E-07	1.48E-06	-7.46E-14

Solution of Second order model Matrix		Matrix of First Order					
X1	12.7157327	Y	X1	X2	X3	X4	
X2	-12.1938114	2990.6	181.9	2884.0	22.0	274.2	
X3	51.4570958	90284.0	30036.4	173090.8	739.7	1743.9	
X4	37.0478864	1440486.4	173090.8	2170330.0	10096.8	224869.1	
X5	-0.02779595	10983.7	739.7	10096.8	83.2	783.7	
X6	7.4234E-08	Inverse of Matrix of First order					
X7	-1.95107888	X1	X2	X3	X4		
X8	-5.1309E-09	0.2359	0.0005	-0.0001	-0.0553		
X9	1.1363E-06	-0.0521	-0.0001	0.0000	0.0121		
X10	-1.9567E-09	2.0811	0.0043	-0.0010	-0.4609		
X11	-0.01129449	0.2281	0.0005	-0.0001	-0.0536		
X12	3.01234997						
X13	-0.01370202						
X14	8.3809E-07						