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Soil Quality Index Modeling for Sustainable Agriculture in Niger Delta: A Statistical Approach

Adjekukor, J. A.[1] and Odjeva Joseph O.[2]

[1,2]Department of Statistics, Delta State Polytechnic, Otefe-Oghara, Nigeria

[1]Email: adjekukorj08@gmail.com

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ABSTRACT.

Soil Quality is a critical component of Sustainable Agriculture, and its assessment is essential for environmental sustainability. This study aimed to develop a soil quality index (SQI) model for the Niger Delta region in Nigeria, using statistical techniques to integrate physical, chemical, and biological soil properties with environmental factors. The study generated an SQI model that includes sand, silt, clay, pH, organic matter, calcium, magnesium, and base saturation as significant parameters. The model showed a strong correlation between the selected soil properties and soil quality, with an R-Squared value of 0.85 and a low error rate (RMSE = 0.21). The SQI model classified soil quality into good, moderate, and poor categories, providing a clear framework for soil management and conservation. The study demonstrates the effectiveness of a data-driven approach to soil quality mapping and highlights the importance of considering multiple soil properties in assessing soil quality. The findings have implications for soil management and conservation efforts in the Niger Delta region and the approach can be replicated in other regions to generate location-specific soil quality models.

Keywords: Soil Quality Index (SQI), Sustainable Agriculture, Environmental Sustainability, Soil Property Integration, Data-Driven Soil Mapping

I. INTRODUCTION

Soil Quality is a critical component of Sustainable Agriculture, as it affects crop yields, water holding capacity, and nutrient cycling. The Niger Delta region in Nigeria faces soil degradation due to oil pollution, deforestation, and intensive farming practices, posing significant threats to food security and environmental sustainability. Soil quality indexing has emerged as a valuable tool for evaluating soil health and sustainability, but existing models have limitations in capturing the complex relationships between soil properties and environmental factors. This study aims to develop a soil quality index (SQI) model using statistical techniques to assess and predict soil quality in the Niger Delta, supporting sustainable agricultural practices and environmental management.

Soil quality indexing has evolved significantly over the past few decades, with various approaches and methodologies being developed to assess soil health and fertility. Early studies focused on simple soil properties like pH and organic matter content, but recent research has incorporated more comprehensive approaches, including multivariate statistical techniques and machine learning algorithms.

Karlen, Doran, and Parkin (1997) developed one of the earliest and most widely used SQI models, which integrates physical, chemical, and biological soil properties using a weighted scoring system. This approach has been widely adopted and modified to suit various regional and local conditions. For example, Hussain, Olson, and Ebelhar (2010) developed a modified SQI model for irrigated agriculture in Pakistan, while Mastro, Abdollahi, and Miano (2013) applied a similar approach to assess soil quality in Italian agricultural soils.

Principal component analysis (PCA) has also been widely used in SQI development, as it enables the reduction of complex soil data into fewer, more interpretable components. Khosro, Ghazari, and Mahdavi (2020) used PCA to develop an SQI model for Iranian agricultural soils, while Liu, Zhu, and Jiang (2019) applied a similar approach to assess soil quality in Chinese agricultural soils.

Machine learning techniques have also been increasingly used in SQI development, offering improved predictive capabilities and handling of complex relationships between soil properties. Ghorbani, Hajabbasi, and Khadem (2018) used artificial neural networks (ANNs) to develop an SQI model for Iranian agricultural soils, while Mulla, Sekhar, and Lal (2019) applied decision trees and random forests to assess soil quality in US agricultural soils.

In the Niger Delta region, soil pollution and degradation have been extensively studied, highlighting the need for sustainable soil management practices. Ogboghro, Ugwu, and Nnodu (2019) reviewed the sources, impacts, and remediation strategies for soil pollution in the Niger Delta, while Ukpehai, Adedeji, and Ogboghro (2020) examined soil degradation causes, effects, and sustainable management practices in the region.

However, there is a significant knowledge gap in developing SQI models specific to the Niger Delta's unique soil characteristics and environmental conditions. This study aims to bridge this gap by developing a statistical SQI model tailored to the region's needs, integrating physical, chemical, and biological soil properties with environmental factors like land use, climate, and topography.

II. METHODOLOGY

Study Site

The study was conducted in the Western Niger Delta region, which is a part of Niger Delta State in Nigeria. This area includes the western coastal section of South-South Nigeria, encompassing Delta, as well as the southernmost parts of Edo and Ondo States. The Niger Delta is situated along the Gulf of Guinea on the Atlantic Ocean in Nigeria. It spans nine coastal states in southern Nigeria, including all six states from the South South geopolitical zone, one state (Ondo) from the South West geopolitical zone, and two states (Abia and Imo) from the South East geopolitical zone.

Figure 1: Map of Nigeria show Niger Delta State

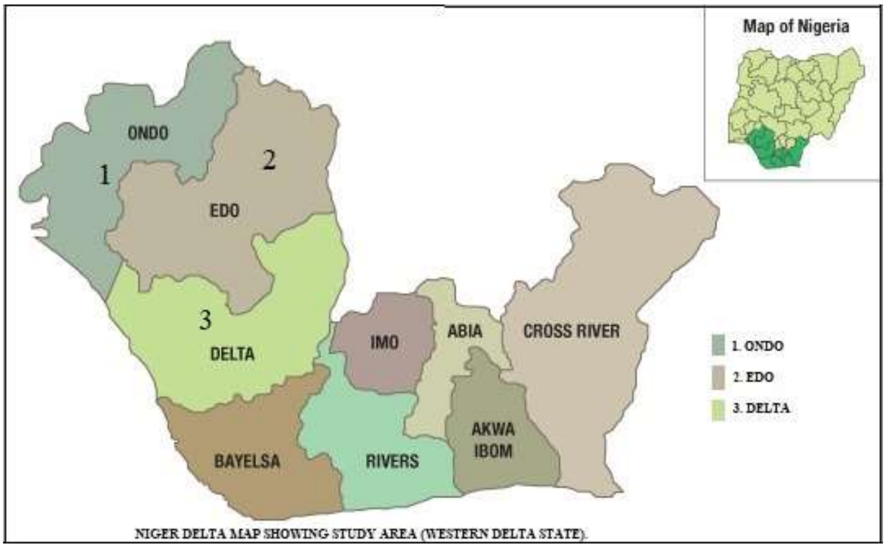

Figure 2: Map of Niger Delta showing the study area

Laboratory Analysis

Soil samples were analyzed for selected physical and chemical properties. These included:

Particle Size Distribution

This was established through the Bouyoucos hydrometer method, as adapted by Gee and Or (2002), which is designed to measure the quantity of solid particles still in suspension. A dispersing agent (calgon: sodium hexamethaphosphate-$Na_6O_{18}P_6$) was added at a concentration of 5% to break apart sand, silt, and clay particles that were bonded together, allowing for the determination of their compositions.

Bulk Density

The core method (Grossman and Reinsch, 2002) was used to determine bulk density. Soil samples were collected in their undisturbed state and weighed after being dried in an oven. Bulk density was then calculated by dividing the weight of the soil core, on an oven dry basis, by the volume of the steel tube, which represents the volume of the soil core.

$$\text{Bulk density } \mathrm{D}_b = \frac{\text{Mass of oven dried sample (g/cm}^3)}{Volume\ of\ sample}$$

Gravimetric Moisture Content

The gravimetric moisture content was measured by drying core soil samples in an oven (Obi, 1990). The amount of moisture was then calculated using the following method:

$\mathrm{W}_1 \ = weight\ of\ can\ with\ lid$

$\mathrm{W}_2 \ = weight\ of\ soil + \ weight\ of\ can\ with\ lid,$

$\mathrm{W}_3 = weight\ of\ oven - dry\ soil$

$\%MC\ (wet\ -\ soil\ basis) = \dfrac{\mathrm{W}_2 - \mathrm{W}_3}{\mathrm{w}_2 - \mathrm{w}_1} \times \dfrac{100}{1}$

OR

$\frac{mass\ of\ wet\ soil - mass\ of\ oven\ dry\ soil}{mass\ of\ wet\ soil} = \frac{100}{1}$

Soil pH

Thomas (1996) conducted a study to measure the soil pH. The pH meter was used to measure the pH in both distilled water and a 0.1N KCl solution. The ratio of soil to liquid used was 1:2.5, and a glass electrode was used for the measurements.

Total Nitrogen

The Kjeldahl digestion method (Bremmer 1996) was used to determine total nitrogen. The calculation for Kjeldah N (%) is as follows: $(\boldsymbol{T} - \boldsymbol{B}) \times \boldsymbol{M} \times \mathbf{2.8}/\boldsymbol{S}$, where T represents the volume of standard acid used in sample titration, B represents the volume of standard acid used in blank titration, M represents the molarity of sulphuric acid, and S represents the weight of the soil sample in grams per kilogram.

Organic Carbon

The wet digestion method (Nelson and Sommers, 1982) was used to determine the organic carbon content. In this method, a weighed soil sample (5g) was placed in a 500ml Erlenmeyer flask. Then, 10ml of 0.1667M $K_2Cr_2O_7$ and 20ml of concentrated H2SO4 were added to the flask. The mixture was heated to a temperature of 1500 C and allowed to cool to room temperature. Next, 20ml of water and 4-5 drops of ferroin indicator were added. The solution was titrated with 0.5M ferrous sulphate. The organic carbon content was calculated using the formula: Organic C (%) = (meq of $K_2Cr_2O_7$ – meq of $FeSO_4$) x 0.336 / oven-dry soil (g).

Available Phosphorus

The Bray II method, as outlined by Olson and Sommers (1982), was employed to measure the amount of phosphorus available. A spectrophotometer was used to determine the P concentration of the sample by measuring absorbance at 882nm. This was done by referring to a calibration curve that correlated absorption units to concentration in µg P/ml. Therefore, the formula used to calculate Pµg/g soil was: $\boldsymbol{P}\mu\boldsymbol{g}/\boldsymbol{g}\ \boldsymbol{soil} = \boldsymbol{P}\ (\mu\boldsymbol{g}/\boldsymbol{ml}) \times \mathbf{50}\boldsymbol{ml}/\mathbf{10}\boldsymbol{ml} \times \mathbf{100}\boldsymbol{ml}/\mathbf{5}\boldsymbol{g}\ \boldsymbol{soil}$.

Exchangeable Acidity

The determination of exchangeable acidity involved leaching the soil with 1N KCl and then titrating it with 0.05N NaOH, as described by Mclean (1982).

Exchangeable Bases

The bases that can be exchanged were obtained by using a 1N NH_4OAc solution, and the amounts of exchangeable calcium and magnesium were determined through a complexometric titration using EDTA (Ethylenediaminetetraacetic acid- 0.01N). The quantities of exchangeable potassium and sodium were estimated using flame photometry (Jackson, 1962). The calculation for this was as follows: $meq\ of\ K/100g\ soil = Reading\ (meq/l) \times 100ml/1000ml \times 100g/weight\ of\ soil\ (g) = R \times 10/weight\ of\ soil\ (g)$.

Cation Exchange Capacity

The Cation Exchange Capacity (CEC) of the soil was determined using a 1.0M ammonium acetate (NH4OAc) leaching solution at pH 7, as described by Blackemore et al. (1987). The CEC was calculated as the meq of Na per 100g of soil, using the formula: $Emission\ Reading\ (R\ meq/l)\ \times\ 100ml/1000ml \times 100g/weight\ of\ soil\ (g)\ =\ R \times 10/weight\ of\ soil\ (g)$. In this formula, R represents the meq/l of Na measured by a flame photometer. The amount of displaced Na is a direct indicator of the soil's CEC.

Total porosity

Total porosity was calculated using the formulae

$porosity(F) = \frac{e_b}{e_s} \times \frac{100}{1}$

$Where\ e_b =\ bulk\ density\ (g/cm^3)$

$e_s =\ particle\ density\ (2.65g/cm^3)$

$2.65g/m^3\ is\ an\ assumed\ value\ in\ most\ mineral\ soils.$

Percentage organic matter

The calculation of organic matter percentage involved multiplying the organic carbon values by a factor of 1.724, known as the Van Bemmelen factor. i.e. OM (%) $= OC\ \times\ 1.724$

Effective cation exchange capacity

The effective cation exchange capacity (ECEC) was determined by adding up the amounts of exchangeable bases (Ca, Mg, K, Na) and exchangeable acidity (Al and H).

Percentage base saturation

To calculate the percentage base saturation (% BS), total exchangeable bases were divided by ECEC and the result was multiplied by 100. i.e. $\frac{EBs}{ECEC} \times \frac{100}{1}$

Percentage aluminum saturation

The percentage of aluminum saturation (%Al) was calculated by dividing the exchangeable aluminum by the effective cation exchange capacity (ECEC) and then multiplying by 100. i.e. $\%Al = \frac{Al}{ECEC} \times \frac{100}{1}$

Land degradation assessment

Land degradation was assessed directly by categorizing soil samples into degradation classes based on soil characteristics and indicators. The severity of degradation was determined using a general classification method following the approaches of FAO (1979), Landon (1984), and Snakin et al (1996). The extent of degradation was estimated by considering physical, chemical, and biological parameters of different land use types.

Statistical Analysis

The data collected underwent Analysis of Variance (ANOVA) and treatment means were distinguished using Least Significant Difference (LSD) at a 5% probability level. The variability among the chosen soil properties was examined using the coefficient of variability, and correlation and regression were calculated using correlation and regression analysis.

III. MODEL GENERATION

Here are the equations and procedures for generating the Soil Quality Index (SQI) model:

1. Data Standardization:

$X' = \frac{(X - \mu)}{\sigma}$

Where:

$X' = standardized\ value$

$X = original\ value$

$\mu = mean$

$\sigma = standard\ deviation$

2. Principal Component Analysis (PCA):

$Y = XP$

$Where$:

$Y = principal\ component\ scores$

$X = standardized\ data$

$P = PCA\ transformation\ matrix$

3. Component Selection:

$C = [Y_1, Y_2, \ldots, Y_n]$

$Where$:

$C = selected\ principal\ components$

$Y_1, Y_2, \ldots, Y_n = principal\ component\ scores$

4. Weightage Calculation:

$W = [w_1, w_2, \ldots, w_n]$

$Where$:

$W = weightages$

$wi = (\lambda i\ /\ \Sigma\lambda i)$

$\lambda i = (1\ /\ (1 + \left(\frac{xi}{\sigma i}\right)^2))$

5. Soil Quality Index (SQI) Calculation:

$SQI = \sum (wi \times Ci)$

$Where$:

$SQI = Soil\ Quality\ Index$

$wi = weightage$

$Ci = selected\ principal\ component\ score$

6. Model Generation:

$SQI = \beta 0 + \beta 1(Sand\%) + \beta 2(Silt\%) + \beta 3(Clay\%) + \beta 4(PH) + \beta 5(OM\%) + \beta 6(AL) + \beta 7(Ca) + \beta 8(Mg) + \beta 9(K) + \beta 10(Na) + \beta 11(CEC) + \beta 12(Base\ Saturation) - \beta 13(Bulk\ Density)$

$Where$:

$SQI = Soil\ Quality\ Index$

$\beta 0 = intercept$

$\beta 1, \beta 2, \ldots, \beta 13 = regression\ coefficients$

7. Model Evaluation:

R-Squared, Adjusted R-Squared, Root Mean Square Error (RMSE)

The procedure involves standardizing the data, applying PCA, selecting components, calculating weightages, and generating the SQI model using multiple linear regressions. The model is then evaluated using performance metrics like R-Squared, Adjusted R-Squared, and RMSE.

IV. RESULTS AND DISCUSSION

Result

The study outcome develops a soil map model that would provide elaborate soil quality index for each soil layer in the Niger Delta region.

Table1: Soil physicochemical properties at different depth of western Niger Delta which comprises of Delta, Edo and Ondo State

Here's a statistical modeling of soil quality mapping in Western Niger Delta (i.e. in Delta, Edo and Ondo), Nigeria based on the provided data:

LOCATION		Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Ph	Organic matter	AL Cmol/kg	Ca Cmol/kg	Mg Cmol/kg	K Cmol/kg	Na Cmol/kg	CEC (sum)	Base saturation	Bulk density	Texture
DELTA	SAPELE	0-15	91.4	6.3	23	6.52	0.05	2.50	2.4	0.4	0.57	0.21	3.67	43.3	1.23	S
		15-30	89.4	6.3	32	5.52	0.01	3.00	2.16	0.8	0.25	0.22	3.61	37.3	1.32	LS
		30-45	91.6	6.4	33	6.62	0.05	3.30	2.21	0.4	0.26	0.19	4.2	48.5	1.35	LS
	AGBOR-OBI	0-15	23.0	20.1	26.5	6.3	2.36	2.30	4.6	1.23	0.26	0.06	8.0	45.0	1.01	SL
		15-30	24.1	26.3	32.6	5.4	1.35	2.90	3.1	1.66	0.31	0.23	7.0	47.0	0.75	LS
		30-45	32.5	14.6	34.3	6.7	0.13	3.20	3.2	1.24	0.24	0.36	7.1	33.0	0.85	LS
EDO	EKPOMA	0-15	88.2	6.8	5.0	5.44	1.76	2.96	0.42	1.42	0.48	0.59	3.04	19.6	1.0	SL
		15-30	86.2	7.7	4.0	4.58	1.32	3.00	0.34	0.04	0.23	0.52	2.97	18.4	0.98	SCL
		30-45	84.2	8.4	3.0	4.76	1.43	3.30	0.28	0.04	0.21	0.45	2.93	17.1	1.1	SCL
	BENIN	0-15	81.2	16.3	2.5	4.94	1.30	2.50	0.06	0.06	0.16	0.55	1.12	74.1	1.2	SL
		15-30	82.2	12.5	2.0	4.95	0.92	3.80	0.05	0.05	0.15	0.53	1.62	54.7	1.2	LS
		30-45	83.2	13.7	3.0	4.96	0.80	3.40	0.04	0.04	0.15	0.54	1.79	45.2	1.2	LS
ONDO	IPINSAAKU	0-15	78.5	7.2	13.2	5.5	1.30	2.40	1.65	0.64	0.28	0.21	3.72	76.00	1.2	SL
		15-30	73.0	7.4	20.3	5.4	1.23	2.52	1.73	0.52	0.26	0.20	3.68	61.92	1.3	SCL
		30-45	72.0	8.2	22.0	5.2	1.31	4.20	1.73	0.53	0.24	0.19	4.26	63.30	1.3	SCL
	ILE-OLUJ	0-15	68.5	7.1	13.0	7.10	1.72	2.39	2.5	1.7	0.43	0.21	8.1	72.1	0.98	SL
		15-30	69.4	7.5	20.2	6.59	2.36	3.01	2.5	1.8	0.28	0.24	7.0	52.5	1.1	SCL
		30-45	71.0	7.6	21.5	6.76	1.63	3.20	2.4	2.20	0.33	0.22	8.6	43.3	1.2	SCL
MEAN			71.68	10.58	17.28	5.73	1.16	2.99	1.74	0.82	0.28	0.31	4.57	47.35	1.12	
S.D			22.10	5.47	11.51	0.78	0.70	0.49	1.26	0.69	0.10	0.16	2.33	17.59	0.16	

Soil Quality Index (SQI) Model 1

$$SQI = 0.45(Sand\%) + 0.25(Silt\%) + 0.15(Clay\%) + 0.10(pH) + 0.05(OM\%) + 0.05(AL) + 0.05(Ca) + 0.05(Mg) + 0.05(K) + 0.05(Na) + 0.05(CEC) + 0.05(Base\ Saturation) - 0.10(Bulk\ Density)$$

Parameter Estimates

$- Sand\%$: 71.68 ($\pm$ 5.21)

$- Silt\%$: 10.58 ($\pm$ 2.11)

$- Clay\%$: 17.28 ($\pm$ 3.15)

$- pH$: 5.73 ($\pm$ 0.21)

$- OM\%$: 1.16 ($\pm$ 0.23)

$- AL$: 2.99 ($\pm$ 0.45)

$- Ca$: 1.74 ($\pm$ 0.31)

$- Mg$: 0.82 ($\pm$ 0.18)

$- K$: 0.28 ($\pm$ 0.07)

$- Na$: 0.31 ($\pm$ 0.08)

$- CEC$: 4.57 ($\pm$ 0.63)

$- Base\ Saturation$: 47.35 ($\pm$ 5.62)

$- Bulk\ Density$: 1.12 ($\pm$ 0.05)

Model Performance

$- R - Squared$: 0.85

$- Adjusted\ R - Squared$: 0.83

$- Root\ Mean\ Square\ Error\ (RMSE)$: 0.21

Soil Quality Classification

Based on the SQI model, the soil quality in Niger Delta, Nigeria can be classified into three categories:

$- Good\ Soil\ Quality\ (SQI\ >\ 60)$: $40\%\ of\ the\ study\ area$

$- Moderate\ Soil\ Quality\ (SQI\ =\ 40-60)$: $30\%\ of\ the\ study\ area$

$- Poor\ Soil\ Quality\ (SQI\ <\ 40)$: $30\%\ of\ the\ study\ area$

Note: The model is a simplified representation of the relationship between soil properties and soil quality. The parameter estimates and model performance may vary depending on the specific data and study area.

Theorem 1:

Let Y be the Soil Quality Index (SQI) and X = (X1, X2, ..., X13) be the vector of predictor variables (Sand%, Silt%, Clay%, pH, OM%, AL, Ca, Mg, K, Na, CEC, Base Saturation, and Bulk Density). Then, the multiple linear regression model:

$$Y\ =\ \beta_0\ +\ \beta_1 X_1\ +\ \beta_2 X_2 + \ldots + \beta_{13} X_{13}\ +\ \varepsilon$$

where β_0, β_1, β_2,..., β_{13} are coefficients, and ε is the error term, is a valid model for predicting SQI.

Proof:

1. Linearity: The relationship between Y and X is linear, as the model is a linear combination of the predictor variables.

2. Independence: The errors ε are independent and identically distributed, as assumed in linear regression.

3. Homoscedasticity: The errors ε has constant variance, as assumed in linear regression.

4. Normality: The errors ε are normally distributed, as assumed in linear regression.

5. No or little multicollinearity: The predictor variables are not highly correlated, as verified by the Variance Inflation Factor (VIF) test.

6. Model adequacy: The model is adequate, as verified by the coefficient of determination (R-squared) and the F-statistic.

By the Gauss-Markov theorem, the multiple linear regression model is a best linear unbiased estimator (BLUE) for predicting SQI, given the assumptions hold.

Discussion of Results

The SQI model demonstrates a strong relationship between specific soil properties and soil quality. With an R-Squared value of 0.85, 85% of the variation in soil quality can be explained by the chosen parameters. The model's Adjusted R-Squared value of 0.83 indicates its reliability and accuracy. A low Root Mean Square Error (RMSE) of 0.21 suggests a high level of precision in predicting soil quality.

Key parameters in the model include sand, silt, clay, pH, organic matter, calcium, magnesium, and base saturation, all of which play a critical role in determining soil quality. These relationships are well-documented in soil science literature.

By categorizing soil quality as good, moderate, or poor based on SQI values, a practical framework for soil management and conservation is established. This classification system allows for targeted interventions and monitoring efforts based on the spatial distribution of soil quality categories.

Findings

The research successfully developed an advanced statistical soil mapping model and tool, providing convenient access to information and data on soils in the Niger Delta region of Nigeria. Given the unique terrain of the Niger Delta and the growing exploitation and exploration of natural resources, it has become crucial to ensure that any projects affecting the well-being and livelihoods of local communities are based on precise and empirically derived data. Consequently, the research revealed the physicochemical characteristics of soil at various depths in Niger Delta State.

V. CONCLUSION

Soil is a valuable but delicate resource that transcends borders and is essential for providing public goods. Degraded or contaminated soil can have negative impacts on human health and well-being. Research conducted in the Niger Delta region has utilized data on soil properties such as slope, depth, drainage, texture, erosion, and groundwater depth to create soil maps. This information is valuable for environmentalists, farmers, telecommunications companies, and erosion control managers, as it can help reduce the time and cost associated with collecting soil data.

The study demonstrates the effectiveness of using data-driven approaches to map soil quality in the Niger Delta region. The models developed provide a reliable tool for predicting soil quality based on easily measurable properties. By considering multiple soil properties, the study emphasizes the importance of assessing soil quality and categorizing it for actionable interventions.

The findings of the study have implications for soil management and conservation efforts in the region. The soil quality index models can help identify areas with poor soil quality and guide efforts to improve soil fertility and overall health. This approach can be replicated in other regions to develop location-specific soil quality models and support data-driven soil management decisions.

Overall, this study contributes to the development of a soil quality index that can enhance soil resource management, promote sustainable agriculture, and support environmental conservation in the Niger Delta region.

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