



An Integrated AHP–Entropy Weighted GOD model with K-Means Clustering for Groundwater Vulnerability Mapping in Akwa Ibom State, Nigeria

Ettiabasi B. Umoren*, Aniekan M. Ekanem, Nyakno J. George and Jewel E. Thomas

Abstract

Groundwater resources in the coastal sedimentary basins of sub-Saharan Africa face severe anthropogenic threats. Conventional groundwater vulnerability overlay models, such as the GOD index, are frequently constrained by subjective parameter weighting and arbitrary index thresholding, which can produce spatial over-smoothing and broad, homogeneous vulnerability classifications. To address these limitations, this study presents an integrated hydrogeophysical framework coupling Multi-Criteria Decision Analysis (MCDA) with unsupervised machine learning. Applied to the heterogeneous coastal sedimentary aquifers of northeastern Akwa Ibom State, Nigeria (encompassing Ini, Ikono, Ibiono Ibom, and Itu LGAs), the methodology utilizes 30 1D Vertical Electrical Soundings (VES), 16 high-resolution 2D Electrical Resistivity Tomography (ERT) profiles, and deep borehole lithology logs to characterize subsurface architecture. A hybrid weighting scheme was established by combining expert-driven Analytic Hierarchy Process (AHP) weights with objective, data-dispersion Information Entropy weights. To eliminate predefined category boundaries, K-means clustering ($k = 2$), evaluated via the Elbow Method, was utilized to naturally partition the continuous vulnerability index into two distinct categories: moderate and low. This clustering was executed on the $30 \text{ m} \times 30 \text{ m}$ raster cells encompassing the entire study area. Consequently, the classification provides a continuous spatial vulnerability assessment across the region, rather than being restricted solely to the 30 Vertical Electrical Sounding (VES) station coordinates. Internal cluster metrics (Silhouette Coefficient = 0.93; Davies–Bouldin Index = 0.14; Calinski–Harabasz Index = 791.50) confirmed strong internal separation and compactness of the model-derived clusters. In comparison, the conventional GOD model classified approximately 95% of the mapped area as Low vulnerability and 5% as Very Low/Negligible, producing a substantially more homogeneous spatial pattern. Single-Parameter Sensitivity Analysis revealed that Groundwater Occurrence (G) is the primary risk determinant (65.67% effective weight), while Overlying Strata Lithology (O) serves as a secondary localized risk regulator (22.43% effective weight). By replacing static thresholds with data-driven cluster separation, this integrated AHP–Entropy and K-means framework offers a reproducible, geophysically constrained approach to regional groundwater vulnerability assessment in complex sedimentary settings.

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1.0 Introduction

Groundwater constitutes the primary source of potable water supply, industrial sustenance, and agricultural irrigation across sub-Saharan Africa, particularly within the coastal and sub-coastal sedimentary basins of the Niger Delta region of Nigeria (MacDonald et al., 2012; Chukwura-Osoagba, 2025; Uwa et al., 2019; George et al., 2025a, b; Ebri et al., 2025). In north-eastern Akwa Ibom State, accelerated urbanization, agricultural intensification, and improper waste disposal infrastructure pose severe threats to sub-surface aquifer systems (Amadi et al., 2010; George et al., 2022a, b, c, d, 2023, 2025c; Uche et al., 2021). Assessing intrinsic groundwater vulnerability; defined as the relative susceptibility of an aquifer system to be adversely affected by an applied contaminant load at the surface (Vrba & Zaporozec, 1994; George et al., 2025a), is essential for proactive water resource management, spatial land-use planning, and the mitigation of anthropogenic degradation (Ndoma et al., 2025).

Among conventional parametric indexing models, the GOD index framework, originally developed by Foster (1987), is widely utilized owing to its parsimonious data requirements and effectiveness in data-scarce environments (Akinlalu et al., 2021). The model relies on three fundamental parameters: Groundwater Confinement (G), Overlying Strata Lithology (O), and Depth to Water Table (D). Despite its global application, recent hydrogeological reviews demonstrate that traditional GOD applications, much like standard DRASTIC or SINTACS models, exhibit significant methodological flaws (MacDonald et al., 2012; Zavridou et al., 2026; Halder et al., 2023): Subjective Weighting which rely on rigid, subjective weighting schemes and arbitrary score splits that fail to account for site-

specific hydrogeological variance and local pollutant transport mechanisms (Malakootian et al., 2020; Chukwuma et al., 2023), and Spatial Over-smoothing where conventional overlay models often generate over-smoothed, highly homogeneous vulnerability maps. This spatial artifact causes widespread Type-II errors, where genuinely vulnerable aquifer zones are misclassified as low-risk (false negatives), thereby misguiding environmental regulatory agencies (Barzegar et al., 2019; Gou & Yan, 2026). To resolve these general methodological problems, contemporary research has pivoted toward modifying standard indices using multi-criteria decision analysis (MCDA) and artificial intelligence (Ali et al., 2026; Hou et al., 2025; Ozegin et al., 2024). Aligning with this paradigm, this study equally represents an integrated hydrogeophysical machine-learning framework, that combines the subjective expert logic of the Analytical Hierarchy Process (AHP) (Saaty, 1980) with the objective data-dispersion sensitivity of Information Entropy Weighting (Shannon, 1948; Echogdali et al., 2022) to form a hybrid parameter weight matrix. This hybrid approach mitigates the individual biases of purely expert-driven or purely data-driven models (Gou & Yan, 2026; Rashid et al., 2026). Recent attempts to optimize index overlay models have integrated subjective AHP with objective statistical weighting tools, such as Shannon's Information Entropy, to capture the intrinsic variance of environmental datasets (Ghazavi & Ebrahimi, 2019; Kazakis & Voudouris, 2017). Yet, these hybrid approaches remain constrained by a second technical limitation: the final vulnerability classification invariably depends on arbitrary, human-defined numerical intervals or slicing techniques (such

as equal intervals and natural breaks). This introduces an element of cognitive bias that can obscure natural geochemical and geoelectrical boundaries. The arbitrary discretization of continuous numerical variables fails to reflect the true mathematical distribution of risk within complex transition zones, where permeable unconfined units grade into low-permeability clays.

To address these challenges, more recent research has explored multi-criteria decision analysis (MCDA) and machine learning techniques for index modification. Combining expert judgment via the Analytic Hierarchy Process (AHP) (Saaty, 1980) with data-driven Information Entropy Weighting (Shannon, 1948) balances professional domain knowledge with statistical data dispersion. Furthermore, unsupervised classification algorithms, such as K-means clustering, offer an empirical method for partitioning continuous vulnerability index (VI) distributions without relying on subjective threshold choices.

While individual decision-support tools, geoelectrical methods, and clustering algorithms have been applied independently in various hydrogeological contexts, a key research question remains regarding their joint integration within heterogeneous coastal sedimentary basins. This study addresses these questions by formulating an integrated hydrogeophysical framework that couples 1D VES, 2D ERT, and borehole data with an AHP–Entropy weighted GOD model and K-means clustering optimized via the Elbow Method (minimizing the Within-Cluster Sum of Squares, WCSS), deployed to partition the study area into statistically sound, non-overlapping vulnerability zones (Ortega et al., 2023; Uzcategui-Salazar et al., 2026). Validated using rigorous internal clustering metrics (Silhouette Coefficient, Davies-Bouldin, and Calinski-Harabasz indices) and comprehensive sensitivity analyses specifically Single-Parameter and Map Removal Sensitivity Analyses (Napolitano & Fabbri, 1996; Lodwick et al., 1990), this hybrid

framework establishes an empirical and statistically viable benchmark for regional hydrogeophysical vulnerability mapping in coastal sedimentary environment of northeastern Akwa Ibom State, Nigeria.

2.0 Location and Hydrogeological Setting of the Study Area

The study area encompasses approximately 1,240 km² and is bound between latitudes 5°05'N to 5°35'N and longitudes 7°35'E to 8°55'E. Elevation ranges from 33 m in the riverine floodplains of Ini to 137 m in the northern uplands. Major land-use activities are predominantly subsistence agriculture and rapidly expanding peri-urban settlements. Groundwater occurs under unconfined to semi-confined conditions, with depths to the water table ranging from 5.1 m to over 45 m. Active boreholes tap into the regional sands at depth ranges of 60 m to 150 m. Total annual precipitation frequently exceeds 2,500 mm (based on 1990–2020 climatic data from the Nigerian Meteorological Agency). Located within the northeastern corridor of Akwa Ibom State, Nigeria, the study area is bounded by the administrative limits of the Ibiono Ibom, Itu, Ikono, and Ini Local Government Areas (LGAs) as shown in Figure 1.

The terrain lies within the Niger Delta sedimentary basin, characterized by a distinct flat-topped topography with gentle slopes that slope toward the Atlantic coast (Chiaghanam et al., 2014; Bem et al., 2026; Udo & Mode, 2013; Inyang et al., 2024a, b, Ekpo et al., 2024). The regional climate is equatorial and humid in nature (George et al., 2010; George, 2020). This features an extended rainy season (from April to October) and a shorter dry spell (from November to March) (George et al., 2020, 2022a, b; Ekanem, 2022; Harry et al., 2020; Eni et al., 2024; Odesa et al., 2026). Total annual precipitation frequently exceeds 2,500 mm, acting as the primary source of active recharge to the shallow unconfined aquifer systems (Udosen et al., 2024a, b, c).

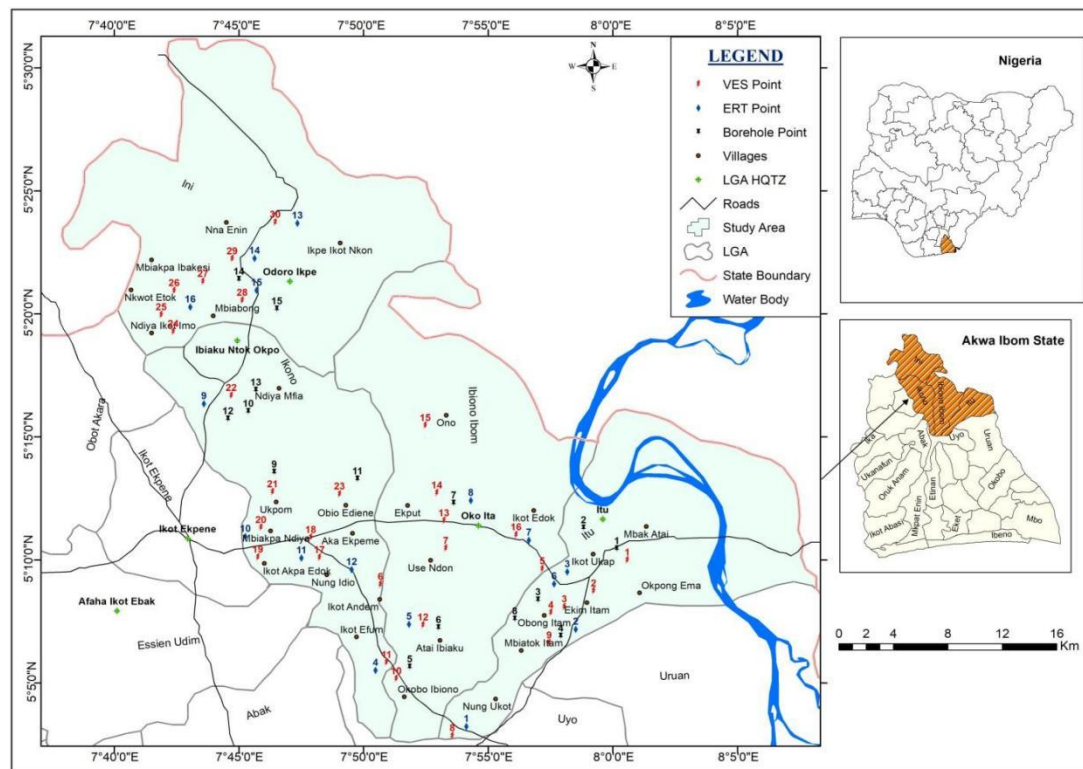


Figure 1: Location map of the study area

Geologically, the study area marks a complex structural transition within the southeastern extension of the Niger Delta Basin, showing highly heterogeneous stratigraphy and complex facies variations (George, 2021a, b). The distribution of the various formations depicted in Figure 2, directly governs the regional hydrogeologic framework (George et al., 2022 a, b, c). The Imo Shale dominates the northern zones of Ibiono Ibom, Ikono, and Ini. This Lower Eocene Formation consists of thick, fissile, impermeable shale beds that restrict vertical fluid flow and form a substantial regional aquitard (Akankpo et al., 2011; Udo et al., 2019; Udo et al., 2023; Ukwuani et al., 2024; Ojeaga, & Osauzou 2024). The Ameki Formation outcrops across the northern margins of Ibiono Ibom and Ini. It features intercalated sandstones, shales, and limestone layers, producing a highly anisotropic aquifer system with variable, fracture-controlled flow regimes (Ogbe & Osokpor, 2019; George et al., 2025a, b, c). The Ogwashi-Asaba Formation extends across major parts of Itu, Ibiono Ibom, Ikono, and Ini, characterized by alternating sequences

of lignite seams, structural clays, and coarse sands. The Benin Formation blankets the southern sectors of Ibiono Ibom and extends into parts of Ikono. This formation consists of highly porous, unconsolidated, continental quartz-sand matrices that offer high groundwater yields but possess very low contaminant attenuation capacities (Adeyemo et al., 2026; Ikpe et al., 2025a, b; Ekanem et al., 2021, 2022, 2024a, b; Udosen et al., 2023, 2024a; Obianwu et al., 2011). Recent Alluvium deposits are concentrated along the northeastern margins of Itu adjacent to the Cross River floodplain. These deposits consist of highly variable sequences of silt, organic clay, and fine-grained gravelly sands.

3.0 Materials and Methods

3.1 1D Vertical Electrical Sounding (VES)

3.1.1 Data Acquisition and Processing

In order to establish a deep, vertical geoelectric stratigraphic framework across the study area, a geophysical survey comprising 30 Vertical Electrical Sounding (VES) stations was conducted across four LGAs between November 2025 and January 2026.

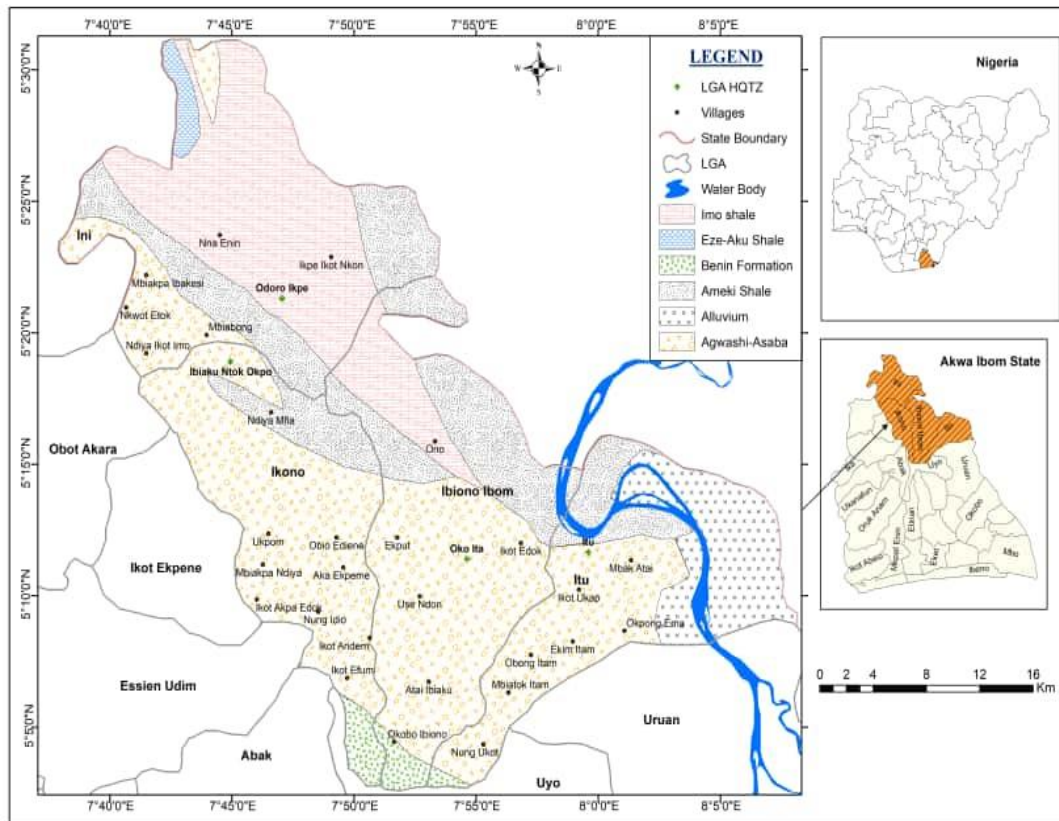


Figure 2: Geologic map of the study area

Data were acquired using an ABEM Terrameter SAS 1000 resistivity meter arranged in a Schlumberger array configuration. Current electrode half-spacing ($AB/2$) ranged from 1 m to 500 m (total current spread $AB = 1,000$ m), ensuring adequate signal penetration depth. Potential electrode half-spacing ($MN/2$) was adjusted to maintain $AB/2 \geq 5MN/2$ in alignment with dipole field assumptions (Dobrin & Savit, 1988). Precise coordinates and elevations for all 30 stations were recorded using a handheld GPS unit (WGS 84, UTM Zone 32N) and presented in Table 1.

The instrument intrinsically measured the subsurface apparent resistance (R_a), defined as the ratio of the potential difference (ΔV) to the injected continuous current (I). To translate these raw resistance values into apparent resistivity (ρ_a), the geometric factor (G), which accounts for the spatial distribution of the electrodes, was applied at each discrete measurement interval (Udosen & George, 2018a). For the Schlumberger array, the

apparent resistivity was mathematically derived in Equation 1, as:

$$\rho_a = \pi \times \left\{ \frac{\left(\frac{AB}{2}\right)^2 - \left(\frac{MN}{2}\right)^2}{MN} \right\} \times R_a \quad (1)$$

where ρ_a is the apparent resistivity, AB is Current electrode spacing, MN is Potential electrode spacing, and R_a Apparent resistance. Data quality control involved four stacked readings per measurement point (retaining observations with standard errors $< 2\%$). Field curves were plotted on log-log scales. Spurious field readings deviating by $> 10\%$ from localized geoelectric trendlines; attributable to surface induction or telluric noise, were identified and removed prior to interpretation. Quantitative 1D inversion was performed using WINRESIST software, initializing starting models with 3 to 5 layers based on partial curve matching. To constrain non-uniqueness (equivalence and suppression effects), layer parameters were constrained against lithological profiles from proximate deep boreholes ($n=8$, located within 50 m to 200 m of selected VES stations).

Iterative damped least-squares inversion proceeded until root-mean-square (RMS) error converged below 5%.

Table 1: Location and Coordinates of VES points

VES NO	Location of Study	Longitude (°)	Latitude (°)
1.	Mbak Atai, Itu	5.1721	7.9980
2.	Okpong Ema Itam, Itu	5.1444	7.9838
3.	Ekim Itam, Itu	5.1337	7.9645
4.	Obong Itam, Itu	5.1380	7.9563
5.	Ikot Ukap, Itu	5.1580	7.9542
6.	Ikot Andem Itam, Itu	5.1488	7.8431
7.	Use Ndon, Ibiono Ibom	5.1781	7.8856
8.	Nung Ukot Itam, Itu	5.0470	7.8906
9.	Mbiatok Itam, Itu	5.1148	7.9593
10.	Okobo, Ibiono Ibom	5.0854	7.8535
11.	Ikot Efum, Ibiono Ibom	5.0963	7.8471
12.	Atai Ibiaku, Ibiono Ibom	5.1215	7.8713
13.	Okoita, Ibiono Ibom	5.1916	7.8851
14.	Ekput, Ibiono Ibom	5.2029	7.8863
15.	Ono, Ibiono Ibom	5.2556	7.8727
16.	Ikot Edok, Ibiono Ibom	5.1821	7.9327
17.	Nung Idio, Ikono	5.1668	7.8028
18.	Aka Ekpeme, Ikono	5.1740	7.7971
19.	Ikot Akpadok Ndiya, ikono	5.1708	7.7557
20.	Mbiakpan Ndiya, ikono	5.1812	7.7552
21.	Ukwongho Ukpom, Ikono	5.1907	7.7548
22.	Ndiya Mfia, Ikono	5.2809	7.7413
23.	Obio Ediene, Ikono	5.2095	7.8161
24.	Ndiya Ikotimo, Ini	5.3150	7.7015
25.	Mbiabong Ikpe, Ini	5.3299	7.6983
26.	Ukwot Etok, Ini	5.3436	7.7093
27.	Mbiakpa Ibakesi, Ini	5.3523	7.7258
28.	Oodoro Ikpe, Ini	5.3540	7.7502
29.	Nna Enin Ikpe, Ini	5.3638	7.7547
30.	Ikpe Ikot Nkon	5.3940	7.7786

3.2 2D Electrical Resistivity Tomography (ERT) Acquisition and Processing

While the 1D VES effectively captured the deep vertical stratigraphy, to resolve shallow lateral structural continuity between discrete VES points, 16 2D ERT profiles (100 m length each; 4 profiles per LGA) were executed using a Wenner electrode array. The Wenner configuration was selected for its high signal-to-noise ratio and strong sensitivity to vertical resistivity boundaries, providing a balanced

trade-off between lateral and depth resolution in near-surface sediments (Udosen & George, 2018b). Minimum electrode spacing (a) was set to 5 m, systematically expanding to 10 m, 15 m, and 20 m to capture pseudo-depths down to approximately 20 m to 30 m.

Contact resistance was tested prior to injection and maintained below 3 k Ω . 2D inversion was conducted using RES2DINV software deploying a smoothness-constrained Gauss-Newton algorithm with L1-norm (blocky)

damping parameters. Data points with RMS residuals >10% were filtered out. Final inverse model sections achieved RMS errors between 2.1% and 4.8%. Figure 3 presents a

representative 2D ERT profile, displaying measured apparent resistivity, calculated apparent resistivity, and the inverted resistivity section (527 Ωm to 2839 Ωm).

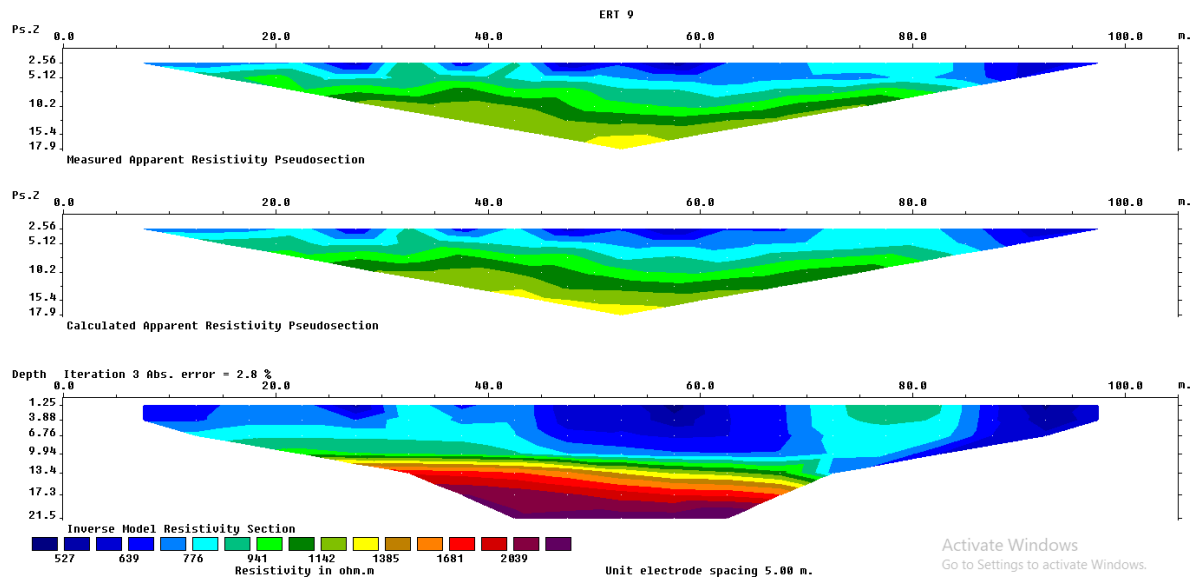


Figure 3: 2D ERT section of the study area

3.3 Borehole Calibration and Correlation

Borehole lithology logs and static water level measurements from 8 deep water wells managed by AK-RUWATSAN were utilized to calibrate geoelectrical layer interpretations (Figure 4). Measured layer resistivities were correlated with lithology as follows:

Low resistivity (<100 Ωm): Impermeable to semi-permeable clay and shale aquitards.

Moderate resistivity (100 - 400 Ωm): Clayey sand and sandy clay

High resistivity (400 - 1,000 Ωm): fine-grained saturated sand and Medium-to-coarse saturated sands.

Very high resistivity (>1,000 Ωm): Dry surficial sand or highly resistive gravelly sand matrices.

3.4 Methodological Workflow

The integrated assessment follows a structured seven-step processing workflow (Figure 5).

3.5 GOD Parameter Derivation and Mapping

The streamlined index proposed by Foster (1987) uses three core criteria to evaluate the

structural vulnerability of the system based on Equation 2 as;

$$iGOD = G \times O \times D \quad (2)$$

where iGOD is the GOD index, G is the groundwater occurrence, O represents the Overlying strata lithology, and D represent the depth to water table. These parameters are assigned notes based on Table 2. The final GOD indices calculated from Equation 2, are assigned ratings into different classes of vulnerability based on Table 3.

1. Groundwater Occurrence (G)

Groundwater occurrence was determined by identifying the structural setting of the aquifer (unconfined, semi-confined, or confined) through the geoelectric sequence constrained by borehole information (George et al., 2025b). Thick, continuous clay-shale sheets over sand zones show confined to semi-confined regimes, while continuous sandy sequences from the surface down show unconfined settings, which carry the maximum vulnerability score (1.0). Ratings assigned to this parameter are based on Table 2.

2. Overlying Strata Lithology (O)

This parameter was extracted from the inverted resistivity ranges of the layers above the target aquifer constrained by borehole information. It categorizes the protective cover into distinct lithological classes. This parameter was assigned note range from 0.4 to 0.8 based on Table 2.

3. Depth to Groundwater (D)

Depth to groundwater was calculated from the upper boundary of the water-bearing layer on the VES profiles constrained by borehole information (George & Thomas, 2024). Shorter vertical distances between the surface and the aquifer diminish attenuation potential, directly increasing the total GOD index score. Note ranging from 0.4 to 1.0 were assigned to this parameter based on Table 2.

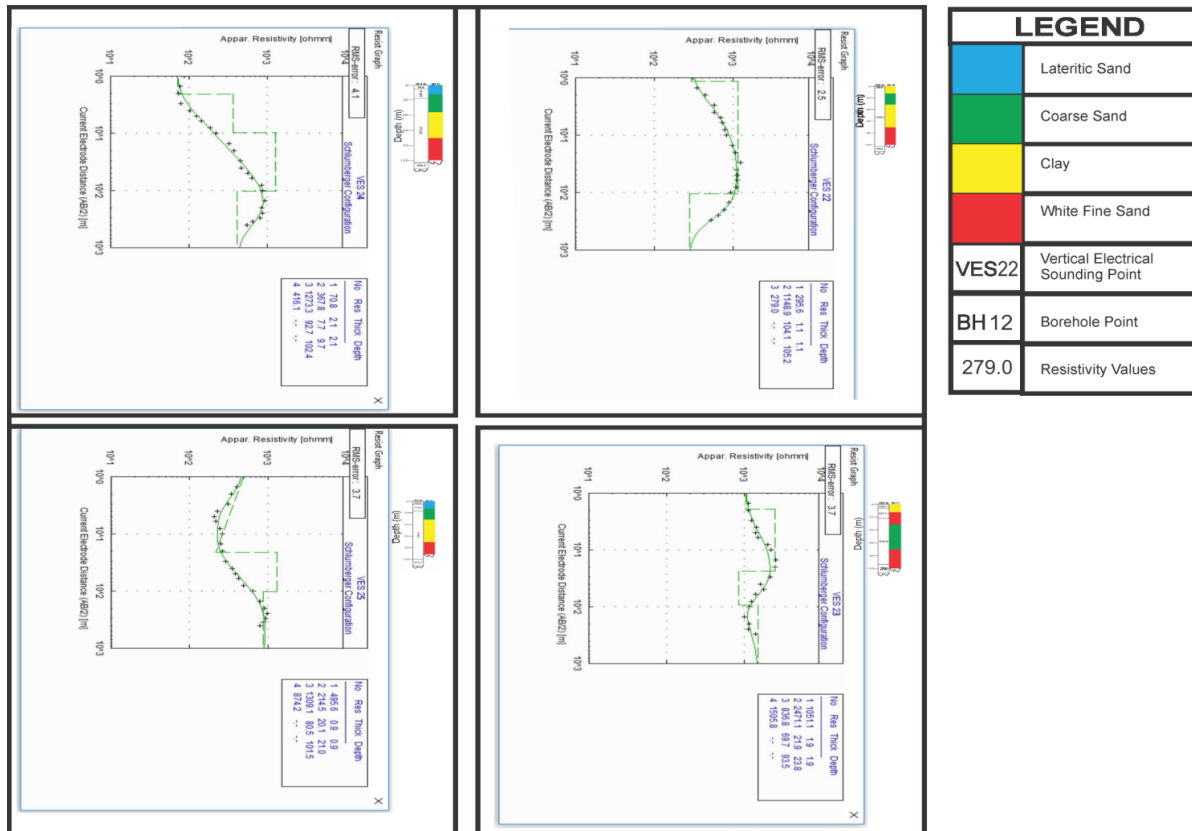


Figure 4: Distribution of deep borehole constrained VES curves in the study area

3.6 Traditional GOD Index Vulnerability Result

The result for streamlined index proposed by Foster (1987) which uses three core criteria to evaluate the structural vulnerability of the system according to Table 2, and is presented on Table 4.

3.7 Hybrid GOD Index for Vulnerability Assessment

The standard GOD model, developed by Aller et al. (1987) for the US EPA, is empirical and uses a simple multiplicative formula based on the ratings presented in Table 1. While this model is reliable, these original weights fail to account for local hydrogeological variances, and classifying

the final map into zones using arbitrary index ranges introduces human bias. This hybrid approach adapts it into a multi-criteria decision-making (MCDM) framework, combining the Analytic Hierarchy Process (AHP) for structured expert judgment, Information Entropy for data-driven variation, and Unsupervised k-Means Clustering for automated zonation, we eliminate these structural flaws and produce a statistically defensive vulnerability assessment. All three GOD thematic layers were standardized to a uniform spatial grid resolution (30 m x 30 m) and projected onto a common spatial reference system. Hydrogeological parameter values were converted into standardized ratings ($r_{ij} \in [1, 10]$)

following the criteria established by Aller et al. (1987).

3.8 AHP Weighting Scheme

Subjective parameter weights (W_j^A) were derived using the Analytic Hierarchy Process (Saaty, 1980). Pairwise comparisons were established by the authors comprising of seasoned Geophysicists and Hydrogeologists

who familiar with the Niger Delta sedimentary basin. Relative importance was assigned using Saaty's 1–9 scale ($G > O > D$), reflecting the primary role of structural confinement in restricting vertical contaminant movement (Table 5).

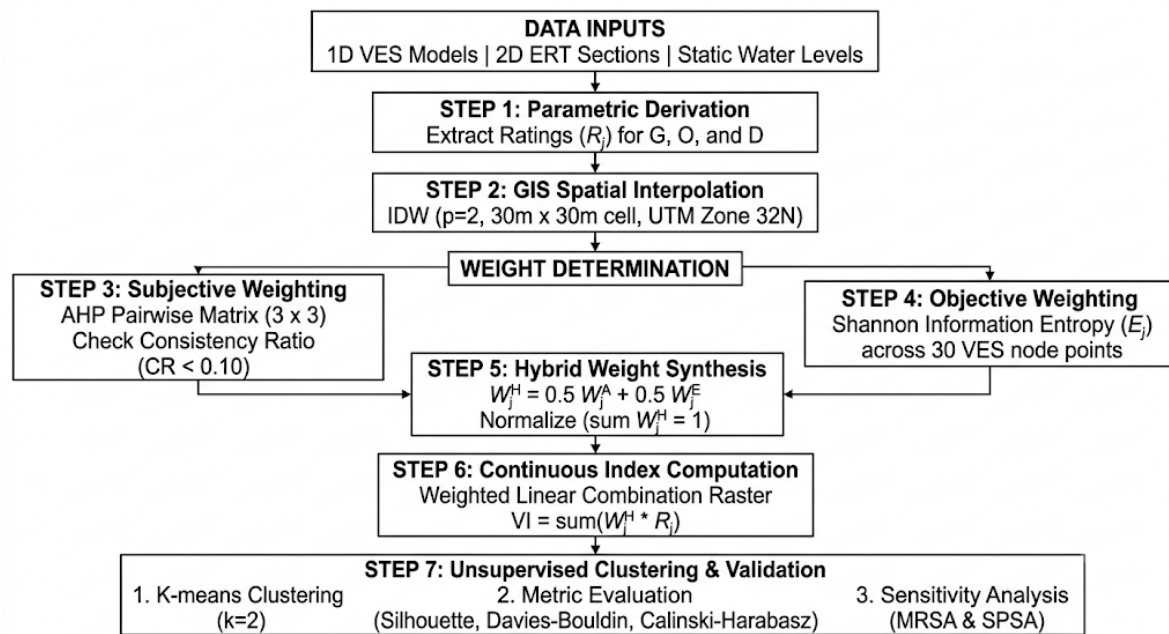


Figure 5: Integrated AHP–Entropy GOD K-Means Workflow

Table 2: Attribute of notes for GOD index model Parameters (Sartika et al., 2020)

Groundwater Occurrence	Note	Overlying strata Lithology (Ω -m)	Note	Depth to aquifer (m)	Note
Non-aquifer	0	<60	0.4	<2	1
Artesian	0.1	60-100	0.5	2-5	0.9
Confined	0.2	100-300	0.7	5-10	0.8
Semi-Confined	0.3-0.5	300-600	0.8	10-20	0.7
Unconfined	0.6-1.0	>600	0.6	20-50	0.6
				50-100	0.5
				>100	0.4

Table 3: GOD Index rating (Foster, 1987)

Vulnerability Class	Index rating
Very Low/Negligible	0.0-0.1
Low	0.1-0.3
Moderate	0.3-0.5
High	0.5-0.7
Extreme	0.7-1.0

Table 4: Traditional GOD index Results

VES NO	Location of Study	Long. (°)	Lat. (°)	G	O	D	iGOD	GVR
1	Mbak Atai, Itu	5.1721	7.998	0.6	0.6	0.5	0.18	Low
2	Okpong Ema Itam, Itu	5.1444	7.9838	0.2	0.6	0.5	0.06	Negligible
3	Ekim Itam, Itu	5.1337	7.9645	0.6	0.5	0.6	0.18	Low
4	Obong Itam, Itu	5.138	7.9563	0.6	0.6	0.5	0.18	Low
5	Ikot Ukap, Itu	5.158	7.9542	0.6	0.6	0.5	0.18	Low
6	Ikot Andem Itam, Itu	5.1488	7.8431	0.6	0.7	0.5	0.21	Low
7	Use Ndon, Ibiono Ibom	5.1781	7.8856	0.3	0.6	0.5	0.09	Negligible
8	Nung Ukot Itam, Itu	5.047	7.8906	0.6	0.7	0.5	0.21	Low
9	Mbiatok Itam, Itu	5.1148	7.9593	0.6	0.6	0.4	0.14	Low
10	Okobo, Ibiono Ibom	5.0854	7.8535	0.6	0.6	0.4	0.14	Low
11	Ikot Efum, Ibiono Ibom	5.0963	7.8471	0.6	0.6	0.5	0.18	Low
12	Atai Ibiaku, Ibiono Ibom	5.1215	7.8713	0.6	0.6	0.5	0.18	Low
13	Okoita, Ibiono Ibom	5.1916	7.8851	0.6	0.6	0.5	0.18	Low
14	Ekput, Ibiono Ibom	5.2029	7.8863	0.6	0.6	0.4	0.14	Low
15	Ono, Ibiono Ibom	5.2556	7.8727	0.6	0.6	0.4	0.14	Low
16	Ikot Edok, Ibiono Ibom	5.1821	7.9327	0.3	0.6	0.4	0.07	Negligible
17	Nung Idio, Ikono	5.1668	7.8028	0.6	0.6	0.5	0.18	Low
18	Aka Ekpeme, Ikono	5.174	7.7971	0.6	0.5	0.5	0.15	Low
19	Ikot Akpadok Ndiya, ikono	5.1708	7.7557	0.6	0.5	0.5	0.15	Low
20	Mbiakpan Ndiya, ikono	5.1812	7.7552	0.6	0.6	0.5	0.18	Low
21	Ukwongho Ukpom, Ikono	5.1907	7.7548	0.3	0.6	0.5	0.09	Negligible
22	Ndiya Mfia, Ikono	5.2809	7.7413	0.3	0.6	0.4	0.07	Negligible
23	Obio Ediene, Ikono	5.2095	7.8161	0.6	0.8	0.5	0.24	Low
24	Ndiya Ikotimo, Ini	5.315	7.7015	0.6	0.6	0.4	0.14	Low
25	Mbiabong Ikpe, Ini	5.3299	7.6983	0.6	0.6	0.4	0.14	Low
26	Ukwot Etok, Ini	5.3436	7.7093	0.6	0.7	0.4	0.17	Low
27	Mbiakpa Ibakesi, Ini	5.3523	7.7258	0.6	0.6	0.5	0.18	Low
28	Odooro Ikpe, Ini	5.354	7.7502	0.6	0.6	0.5	0.18	Low
29	Nna Enin Ikpe, Ini	5.3638	7.7547	0.6	0.6	0.5	0.18	Low
30	Ikpe Ikot Nkon	5.3940	7.7786	0.3	0.7	0.5	0.11	Low

Table 5: Pairwise comparison decision matrix and derived AHP weights (W_j^A)

Parameter	Groundwater Occurrence (G)	Overlying Strata Lithology (O)	Depth to water table (D)	Priority Vector (AHP Weight, W_j^A)
G	1.0000	3.0000	5.0000	0.6479
O	0.3333	1.0000	2.0000	0.2299
D	0.2000	0.5000	1.0000	0.1222
Column Sum	1.5333	4.5000	8.0000	1.0000

The principal eigenvalue (λ_{max}) was subsequently calculated to derive the subjective weight (W_j^A) for each respective parameter using Equation 3.

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n \frac{(Aw)_i}{w_i} = 3.0039 \quad (3)$$

where λ_{max} is the principal eigenvalue of the matrix and n is the number of evaluated parameters.

Random Index (RI): for $n = 3$, $RI = 0.58$ (Saaty, 1980).

To verify the logical consistency of the expert judgments, the Consistency Index (CI) and Consistency Ratio (CR) were calculated using Equations 4 and 5 respectively:

$$CI = \frac{\lambda_{max} - n}{n - 1}, \quad (4)$$

where CI is the Consistency Index, λ_{max} is the principal eigenvalue of the matrix and n is the number of evaluated parameters.

$$CI = \frac{3.0039 - 3}{3 - 1} = 0.00196$$

$$CR = \frac{CI}{RI}, \quad (5)$$

where CR is the Consistency Ratio, CI is the Consistency Index, and RI is the Random Index.

$$CR = \frac{0.00196}{0.58} = 0.00338 \text{ (0.34\%)}$$

Since $CR < 0.10$ (10%), the pairwise comparison matrix displays acceptable consistency.

3.9 Information Entropy and Hybrid Weight Calculation

Objective parameter weights (W_j^E) were determined via Shannon Information Entropy (Shannon, 1948) evaluated across the $m = 30$ discrete VES station observation points.

Parameter values (x_{ij}) were normalized to project proportions (p_{ij}) as in Equation 6:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{30} x_{ij}} \quad (6)$$

Normalized entropy (E_j) Equation 7, and objective weights (W_j^E) Equation 8, were calculated using entropy constant: $k = \frac{1}{\ln(30)} \approx 0.2940$,

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^m p_{ij} \ln(p_{ij}) \quad (7)$$

$$W_j^E = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (8)$$

To combine expert logic (W_j^A) with objective data dispersion (W_j^E), linear hybrid weights (W_j^H) were derived using an equal linear synthesis weighting ($\alpha = 0.5$) as shown in Equation 9.:

$$W_j^H = 0.5W_j^A + 0.5W_j^E \quad (9)$$

After linear synthesis, weights were normalized so that $\sum W_j^H = 1.0$, yielding final model weights as presented in Table 6.

3.10 Vulnerability Index (VI) Computation and GIS Interpolation

The continuous hybrid Vulnerability Index (VI) map was computed using weighted linear combination overlay in ArcGIS 10.8 using Equation 10:

$$VI = \sum_{j=1}^3 W_j^H \times R_j = (0.6930 \times R_G) + (0.1821 \times R_O) + (0.1250 \times R_D) \quad (10)$$

where W_j^H is the comprehensive weight and R_j ; R_G , R_O , and R_D represent the spatial raster layers of parameter ratings interpolated via Inverse Distance Weighting (IDW, power = 2, spatial resolution = 30 m $\times$ 30 m, UTM Zone 32N projection).

Table 6: Summary of Information Entropy calculations, objective weights, AHP weights, and finalized linear hybrid weights

GOD Parameter	Sum ($\sum x_{ij}$)	Normalized Entropy (e_j)	Divergence Value ($d_j=1-E_j$)	Objective Weight (W_j^E)	AHP Weight (W_j^A)	Multiplicative Hybrid Weight (W_j^H)	Linear Hybrid Weight ($0.5W_j^A + 0.5W_j^E$)	Percentage Weight
Groundwater occurrence (G)	16.400	0.99145	0.00855	0.7268	0.6479	0.9105	0.6874	69.30%
Overlying Lithology (O)	18.300	0.99859	0.00141	0.1200	0.2299	0.0533	0.1750	18.21%
Depth to water Table (D)	14.200	0.99820	0.00180	0.1532	0.1222	0.0362	0.1377	12.50%
Total	—	—	0.01176	1.0000	1.0000	1.0000	1.0000	100%

3.11 Unsupervised K-Means Clustering and Internal Validation

Rather than applying predefined index class intervals, unsupervised K-means clustering (scikit-learn implementation in Python 3.10) was applied directly to the continuous VI raster values. Algorithm setup parameters included: initialization method = k-means++, n_init = 10, maximum iterations = 300, convergence tolerance = 10^{-4} , random seed = 42. Continuous VI-pixel values were standardized using min-max scaling prior to execution.

3.11.1 Elbow Plot method

Rather than relying on prescribed categorical splits, the optimal number of vulnerability zones (k) was determined empirically using the Elbow Method (Thorndike, 1953; Kaufman & Rousseeuw, 1990). This statistically zonation effectively drew strict boundaries between distinct vulnerability classes. The K-Means algorithm processed the VI-pixel values, automatically grouping them by minimizing the within-cluster variance (Within-Cluster Sum of Squares) according to Equation 11. The algorithm drew strict, statistically boundaries between the vulnerability classes.

$$WCSS = \sum_{i=1}^k \sum_{x \in C_i} \|x - \mu_i\|^2 \quad (11)$$

3.11.2 Clustering Performance and Internal Validation Metrics

The structural integrity, compactness, and separation of the derived K-means vulnerability zones was assessed. Cluster separation and compactness were evaluated using three internal

validation metrics: the Silhouette Coefficient (Rousseeuw, 1987), the Calinski-Harabasz (C-H) index (Caliński and Harabasz, 1974), and the Davies-Bouldin (D-B) index (Davies and Bouldin, 1979).

1. Silhouette Coefficient (S): Evaluates cluster cohesion versus separation (ranges from -1 to +1; higher values indicate distinct separation).
2. Davies-Bouldin Index (DBI): Evaluates average similarity between each cluster and its most similar counterpart (lower values closer to 0.0 indicate tighter compactness and wider separation).
3. Calinski-Harabasz Index (CHI): Ratio of total between-cluster variance to within-cluster variance (higher values reflect distinct cluster separation).

3.12 Sensitivity Analysis of the Hybrid GOD Index

To assess structural model behavior, both Map Removal Sensitivity Analysis (MRSA) and Single-Parameter Sensitivity Analysis (SPSA) were executed across all 30 sounding stations.

3.12.1 Map Removal Sensitivity Analysis

The map removal sensitivity analysis (MRSA) tests the global vulnerability of the entire model design to the exclusion of individual parameters. The sensitivity measure (S_i) is determined by equation 12 as:

$$S = \frac{|V - V_i|}{V} \times 100 \quad (12)$$

where V is the unperturbed vulnerability index

calculated using the complete set of parameters and V_i is the perturbed vulnerability index calculated with the i -th parameter layer removed.

3.12.2 Single parameter sensitivity analysis

To quantify the actual structural impact of individual hydrogeological layers and evaluate how much variation in field data shifts the vulnerability index, a Single-Parameter Sensitivity Analysis (SPSA) was performed based on the empirical formulation proposed by Napolitano and Fabbri (1996). The SPSA computes an Effective Weight (W_i) for each parameter at every distinct sounding station using equation 13.

$$W_i = \left(\frac{X_i \times P_i}{GV} \right) \times 100 \quad (13)$$

where X_i is the raw sub-parameter rating score at a specific sounding location (G, O, or D), P_i is the structural theoretical weight assigned to that parameter by the hybrid framework and GV is the total baseline composite vulnerability index score computed for the location. By comparing the mean realized effective weights against the initial theoretical weight settings, the true diagnostic power of each layer is explicitly validated.

4.0 Results and Discussions

4.1 Field Geophysical Inversion Results

Interpretation of the 30 VES station inversion models revealed a multi-layered subsurface structure comprising 3 to 5 geoelectrical layers. Table 7 summarizes station-by-station geoelectrical parameters and hydrogeological layer interpretations.

Table 7: Summary of 1D VES geoelectrical inversion interpretations across the study area

VES NO	VES Location	Long. (°)	Lat. (°)	Elevation (m)	Layer number	Resistivity (Ω m)	Thickness (m)	Layer Dep(m)	Lithology
1	Mbak Atai, Itu	5.1721	7.998	97	1	85.6	5.1	5.1	Clay
					2	2612.4	83.2	88.3	Gravelly sand
					3	674.5			Fine Sand
2	Okpong Ema Itam, Itu	5.1444	7.9838	102	1	380.9	0.6	0.6	Clayey Sand
					2	1053.1	28.9	29.6	Coarse Sand
					3	2488.1	48.3	77.8	Gravelly Sand
					4	65.3			Clay
3	Ekim Itam, Itu	5.1337	7.9645	82	1	301.1	0.9	0.9	Clayey Sand
					2	81.2	20.4	21.2	Clay
					3	627.1	72.4	93.6	Fine Sand
					4	126.0			Sandy clay
4	Obong Itam, Itu	5.138	7.9563	104	1	186.2	2.8	2.8	Sandy clay
					2	767.2	15.9	18.7	Fine Sand
					3	2608.9	70	88.7	Gravelly sand
					4	1120.5			Coarse Sand
5	Ikot Ukap, Itu	5.158	7.9542	76	1	991.3	2.0	2.0	Fine Sand
					2	2407.6	97.5	99.4	Gravelly Sand
					3	1628.1			Coarse Sand
6	Ikot Andem Itam, Itu	5.1488	7.8431	78	1	2109.7	1.7	1.7	Gravelly sand
					2	241.1	72.5	74.1	Clayey Sand
					3	845.0			Fine Sand
7	Use Ndon, Ibiono	5.1784	7.8856	114	1	686.2	0.7	0.7	Fine Sand
					2	273.5	6.1	6.8	Clayey Sand
					3	1807.6	64.7	71.4	Coarse Sand
					4	239.1			Clayey Sand

8	Nung Ukot Itam, Itu	5.0474	7.8906	76	1	147.4	0.9	0.9	Sandy clay
					2	1873	11.2	12.1	Coarse Sand
					3	296.0	69.9	82	Clayey Sand
					4	1669.3			Coarse Sand
9	Mbiatok Itam, Itu	5.1148	7.9593	99	1	335.5	1.7	1.7	Clayey Sand
					2	1318.4	28.5	30.2	Coarse Sand
					3	2253.6	84.1	114.3	Gravelly sand
					4	696.2			Fine Sand
10	Okobo, ibiono	5.0854	7.8535	78	1	442.6	3.5	3.5	Fine Sand
					2	1280.2	7.5	11	Coarse Sand
					3	3070.7	89.9	100.9	Gravelly sand
					4	818.3			Fine Sand
11	Ikot Efum, Ibiono	5.0963	7.8471	85	1	2207.0	0.7	0.7	Gravelly sand
					2	403.6	5.4	6.1	Fine Sand
					3	2801.5	72.3	78.4	Gravelly sand
					4	424.9			Fine Sand
12	Atai Ibiaku, Ibiono	5.1215	7.8713	90	1	389.0	4.8	4.8	Clayey Sand
					2	1310.1	92.1	96.8	Coarse Sand
					3	1609.2			Gravelly sand
13	Okoita, Ibiono	5.1916	7.8851	90	1	452.6	1.9	1.9	Fine Sand
					2	2394.9	86.8	88.7	Gravelly sand
					3	429.0			Fine Sand
14	Ekput, Ibiono	5.2029	7.8863	90	1	575.4	1.8	1.8	Fine Sand
					2	1283.1	28.3	30.2	Coarse Sand
					3	2001.9	91.7	121.8	Gravelly sand
					4	901.6			Fine Sand
15	Ono, Ibiono	5.2556	7.8727	100	1	1119.1	3.4	3.4	Coarse Sand
					2	743.0	25.7	29.1	Fine Sand
					3	2211.0	73.8	103	Gravelly sand
					4	1157.4			Coarse Sand
16	Ikot Edok, Ibiono	5.1821	7.9327	86	1	998.8	6.5	6.5	Fine Sand
					2	1450.8	121.2	127.7	Coarse Sand
					3	387.0			Clayey Sand
17	Nung Idio, Ikono	5.1668	7.8028	99	1	210.6	0.7	0.7	Clayey Sand
					2	1046.2	22.3	23.1	Coarse Sand
					3	1791.7	61.7	84.8	Gravelly sand
					4	454.1			Fine Sand
18	Aka Ekpeme, Ikono	5.174	7.7971	104	1	866.6	5.0	5.0	Fine Sand
					2	223.1	20.8	25.8	Clayey Sand
					3	189.9	48.5	74.3	Sandy Clay
					4	944.9			Fine Sand
19	Ikot Akpa Edok, Ikono	5.1708	7.7557	95	1	217.0	1.0	1.0	Clayey Sand
					2	94.5	75.2	76.2	Clay
					3	490.8			Fine Sand
20	Mbiakpan Ndiya, Ikono	5.1812	7.7552	103	1	530.2	1.4	1.4	Fine Sand
					2	145.4	5.7	7.1	Sandy clay
					3	2198.4	85.6	92.7	Gravelly sand

						4	906.0			Fine Sand
21	Nkwongho Ikono	Ukpom,	5.1907	7.7548	113	1	642.3	1.1	1.1	Fine Sand
						2	342.2	11.7	12.9	Clayey Sand
						3	1350.4	71.7	84.6	Coarse Sand
						4	312.4			Clayey Sand
22	Ndiya Mfia, Ikono		5.2809	7.7413	127	1	295.6	1.1	1.1	Clayey Sand
						2	1148.9	104.1	105.2	Coarse Sand
						3	279.0			Clayey Sand
23	Obio Ediene, Ikono		5.2095	7.8161	60	1	1051.1	1.9	1.9	Coarse Sand
						2	2471.1	21.9	23.8	Gravelly sand
						3	836.8	69.7	93.5	Fine Sand
						4	1505.8			Coarse Sand
24	Ndiya Ikot Imo, Ini		5.315	7.7015	135	1	70.8	2.1	2.1	Clay
						2	367.8	7.7	9.7	Clayey Sand
						3	1273.3	92.7	102.4	Coarse Sand
						4	416.1			Fine Sand
25	Mbiabong Ikpe, Ini		5.3299	7.6983	137	1	495.6	0.9	0.9	Fine Sand
						2	214.5	20.1	21	Clayey Sand
						3	1309.1	80.5	101.5	Coarse Sand
						4	874.2			Fine Sand
26	Ukwot Etok, Ini		5.3436	7.7093	130	1	199.7	4.5	4.5	Sandy clay
						2	996.7	43.2	47.7	Fine Sand
						3	333.9	72.6	120.3	Clayey Sand
						4	750.0			Fine Sand
27	Mbiakpa Ibakesi, Ini		5.3523	7.7258	119	1	1334.1	0.7	0.7	Coarse Sand
						2	411.8	9.7	10.4	Fine Sand
						3	2491.6	68.1	78.6	Gravelly sand
						4	580.3			Fine Sand
28	Odoro Ikpe, Ini		5.354	7.7502	117	1	1299.4	0.8	0.8	Coarse Sand
						2	462.5	6.3	7.1	Fine Sand
						3	2516.8	33.0	40.0	Gravelly sand
						4	1404.3	56.1	96.2	Coarse Sand
						5	478.6			Fine Sand
29	Nna Enin Ikpe, Ini		5.3682	7.7547	53	1	160.5	1.9	1.9	Sandy clay
						2	45.8	7.3	9.3	Clay
						3	562.2	16.1	25.4	Fine Sand
						4	2883.6	73.6	98.9	Gravelly sand
						5	791.9			Fine Sand
30	Ikpe Ikot Nkon, Ini		5.394	7.7786	33	1	353.6	2.2	2.2	Clayey Sand
						2	68.3	39.9	42.1	Clay
						3	180.2	51.6	93.8	Sandy clay
						4	931.5			Fine Sand

4.2 Geoelectrical and Lithological Stratigraphy by local government (based on Table 7)

Geoelectrical profiles constrained with near deep borehole lithology, display strong spatial variance reflecting regional geological transitions:

Southern Sands (Itu and Ibiono Ibom): Dominated by thick, highly resistive gravelly sand horizons (1,053.1-3,070.7 Ω m) within the Benin Formation (e.g., VES 1, 5, 10, 11). These

highly permeable sand formations extend down to depths >100 m beneath thin topsoils.

Northern Aquitards (Ikono and Ini): Marked by thick, low-resistivity clay and shale intercalations associated with the Imo Shale and Ameki formations. Notable aquitard units occur at VES 19 (Ikot Akpa Edok: 94.5 Ω .m clay aquitard from 1.0 m to 76.2 m depth), VES 24 (Ndiya Ikot Imo: 70.8 Ω .m surficial clay), and VES 29 (Nna Enin Ikpe: 45.8 Ω .m clay layer). These low-resistivity layers function as regional aquitards, restricting vertical fluid flow.

These 1D structural interpretations are validated continuously in the spatial domain by the 16 high-resolution 2D ERT profiles (Figure 3), which effectively bridge the lateral lithological gaps between discrete sounding stations.

4.3 Descriptive Statistics of Mapped GOD Parameters

Parameter ratings across the 30 VES locations yielded the following distribution metrics (based on table 7):

Groundwater Occurrence (G): Mean = 0.547, Standard Deviation = 0.111. 83.3% of stations (n=25) exhibit G=0.6 (unconfined to semi-confined conditions in coastal sands), while 16.7 (n=5; VES 2, 7, 16, 21, 22) show G=0.2-0.3 (confined/artesian conditions beneath clay layers).

Overlying Strata Lithology (O): Mean = 0.610, Standard Deviation = 0.063. Ratings ranged from 0.5 (clayey sand/sandy clay) to 0.8 (coarse gravelly sand).

Depth to Water Table (D): Mean = 0.473, Standard Deviation = 0.058. Ratings ranged from 0.4 (>50 m water table depth on uplands) to 0.6 (10-20 m depth in low-elevation riverine plains).

4.4 Interpretation of 2D ERT Profiles

Figure 3 presents one of the 16 2D ERT profiles acquired during the survey. This tomogram maps the spatial distribution of subsurface resistivity along the selected transect. Analyzing this profile alongside the others acquired for the

study area allows for the mapping of structural weak points (such as fractures or missing clay layers) across the study area, providing the spatial raw data required for the eventual vulnerability zonation. (Thomas et al., 2020)

These 2D tomograms were consolidated on the 1D VES curves to validate geoelectric parameters (such as, groundwater occurrence, depth to water table, and overlying layer lithology from the specific resistivity range of the protective aquitard to effectively drive the hybrid AHP–Entropy weighting and K-Means clustering model.

4.5 Traditional GOD Index Assessment

Calculating traditional iGOD values ($G \times O \times D$) across the 30 VES points yielded scores between 0.060 and 0.240. Categorized according to Foster (1987) thresholds (Table 3):

Very Low / Negligible Vulnerability (iGOD < 0.10): 5 VES stations (16.67% of sampling points: VES 2, 7, 16, 21, 22).

Low Vulnerability (iGOD = 0.10-0.30): 25 VES stations (83.33% of sampling points: VES 1, 3–6, 8–15, 17–20, 23–30).

Interpolating traditional index scores across the continuous GIS domain resulted in approximately 95% area coverage categorized as Low vulnerability and 5% as Very Low/Negligible (Figure 6). This reflects spatial over-smoothing inherent in applying standard static threshold ranges to product-based index scores in regional sedimentary environments.

4.6 Cluster Optimization and Vulnerability Zonation

4.6.1 The Elbow plot Method

The Within-Cluster Sum of Squares (WCSS), or cluster inertia, was evaluated across a spectrum of k values ranging from 1 to 7 as shown in Figure 7. Figure 7 shows a sharp, definitive mathematical inflection point occurring at exactly k = 2, where the WCSS aggressively drops from its maximum baseline value down to approximately 0.01.

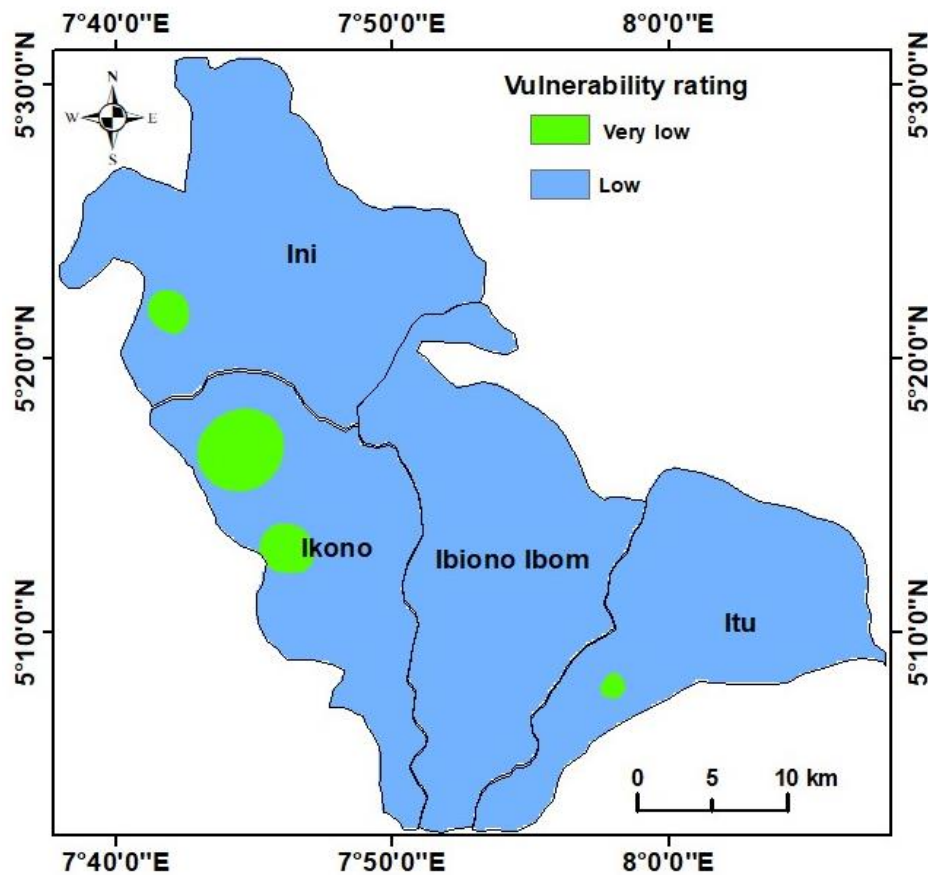


Figure 6: Traditional GOD index vulnerability map

Beyond this optimal threshold ($k > 3$), the mathematical curve exhibits an absolute flatline effect, yielding virtually zero further reduction in internal cluster variance. This flatline behavior indicates that configuring the model to partition the study area into three or more classes would cause severe statistical overfitting. Forced over-clustering ($k = 3$) would compel the algorithm to fragment highly uniform hydrogeological profiles into artificial sub-classes based on negligible, non-critical background noise. Therefore, a dual-cluster layout ($k = 2$) is mathematically established as the most parsimonious framework, ensuring the model maximizes internal consistency while remaining rooted in actual field data constraints.

4.6.2 Clustering Performance and Internal Validation Metrics of hybrid GOD index

The summary of the empirical results of the clustering performance and internal validation metrics is given in Table 8. The Silhouette Coefficient evaluates how close each sampling point is to its assigned cluster relative to the neighboring cluster and was calculated as 0.93 (Table 8). Achieving a 0.93 indicate strong internal separation. This provides strong mathematical backing for the clear boundaries shown on the final groundwater vulnerability map. The Davies-Bouldin Index measures the maximum similarity between each cluster and its most similar counterpart, where lower scores indicate better clustering. The model yielded a low score of 0.14. Because this metric decreases toward 0.0 as clusters become more tightly packed internally and further apart from each other, a score of 0.14 confirms that the variance within the Low and Moderate vulnerability zones is very small compared to the clear gap between them (Davies and Bouldin, 1979). This suggest that any random sample location categorized as "Low" shares nearly identical aquifer characteristics with its cluster peers, while remaining completely distinct from any location categorized as "Moderate".

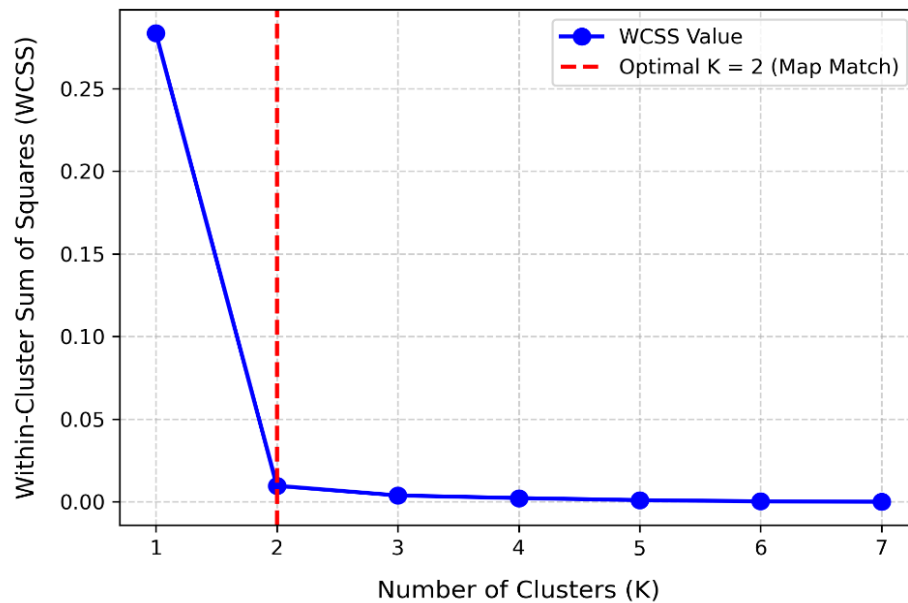


Figure 7: Elbow Plot of Within-Cluster Sum of Squares (WCSS) versus Cluster Count ($k = 1$ to 7)

Table 8: K-Means Internal Cluster Validation Performance Summary

Cluster Metric	Metric Value	Theoretical Range	Interpretation
Silhouette Coefficient	0.93	-1.0 to $+1.0$	Indicates strong internal separation between cluster centroids.
Davies-Bouldin Index (DBI)	0.14	0.0 to ∞	Low value confirms high internal cluster compactness.
Calinski-Harabasz Index (CHI)	791.50	0.0 to ∞	High ratio reflects high between-cluster to within-cluster variance.
Final Residual Inertia (WCSS)	0.02	Minimization $\rightarrow$ 0.0	Low residual variance within assigned cluster groups.

The model produced a high Calinski-Harabasz Index of 791.50. This large number indicates that the distance separating the average center point (centroid) of the Low-vulnerability cluster from the Moderate-vulnerability cluster is massive when compared to the tiny scattering of individual points around those centers. This high score suggests that the algorithm is consistent with, repeatable mathematical partitioning of the field data (Caliński & Harabasz, 1974). The low WCSS value suggests that the algorithm has eliminated random background noise. It provides strong mathematical backing for the final vulnerability map, ensuring that the zoning boundaries reflect clear, distinct, and uniform physical risk profiles across the study area.

However, the present validation evaluates the internal statistical structure of the vulnerability classes rather than independent contaminant occurrence.

4.7 Hybrid AHP-Entropy Weighted GOD Mapping with K-Means

The groundwater vulnerability map generated by using the unsupervised K-means clustering of the optimized hybrid AHP-Entropy GOD index, delineates two separate vulnerability zones (low, moderate) across the study area (Figure 8). The study area is overwhelmingly characterized by a Moderate (light green color) groundwater vulnerability rating. This Moderate vulnerability zone accounts for approximately 70% of the analyzed 30 VES data and covers approximately

70% of the geographical area (868 km²). From a hydrogeological standpoint, this sprawling baseline uniformity is a direct artifact of the underlying lithological and structural stability captured in the dataset. The predominant parameters across this region present a consistent spatial profile of Groundwater occurrence rating fixed at 0.6 (indicative of semiconfined conditions), Overlying Strata Lithology rating consistent at 0.6 (typical of mixed fine-to-medium sand) and Depth to Water Table rating hovering between 0.4 and 0.6 (Table 2).

When processed through the unsupervised K-means clustering engine, these highly dense, recurrent data nodes naturally coalesce into the dominant regional cluster. This points to a consistent, moderate capacity for sub-surface transmission of surface-derived contaminants across the major portions of all four LGAs.

Interrupting this regional Moderate matrix are isolated, discrete pockets classified under a Low vulnerability rating (blue colour). These enclaves occur as localized islands distributed strategically across the study area, viz: two major hydrogeological depressions/zones in central and western Ini LGA, A highly pronounced, elongated low-vulnerability corridor trending North-South across western Ikono LGA, alongside minor peripheral buffer zones at its southern boundary and near the border of Ibiono Ibom and Minimal, isolated circular expressions within central Itu LGA and the extreme southern riverine boundary of Ibiono Ibom.

The spatial genesis of these Low vulnerability zones is fundamentally explained by the Single-Parameter Sensitivity Analysis (SPSA). The SPSA suggests that the Groundwater Occurrence parameter shows comparatively greater sensitivity 65.67% effective weight in determining final composite risk indices.

Summarily, applying the linear hybrid weights ($W_G^H = 0.6930$, $W_O^H = 0.1821$, $W_D^H = 0.1250$) to the normalized parameter rating layers produced a continuous Vulnerability Index (VI) surface

with scores ranging from 0.224 to 0.558. Evaluating cluster inertia (WCSS) across $k = 1$ to 7 revealed a clear inflection point ("elbow") at $k=2$ (Figure 7), where WCSS dropped sharply from 0.185 to 0.021. Increasing k beyond 3 produced negligible variance reduction, supporting $k=2$ as a parsimonious cluster configuration for the continuous VI distribution. K-means clustering ($k=2$) partitioned the study area into two distinct vulnerability classes (Figure 6):

1. Low Vulnerability Cluster: Centroid VI = 0.285. Encompasses 9 VES stations (30.0% of points) and covers approximately 30% of the geographical area (372 km²).

2. Moderate Vulnerability Cluster: Centroid VI = 0.482. Encompasses 21 VES stations (70.0% of points) and covers approximately 70% of the geographical area (868 km²).

4.8 Overall Study Area Vulnerability Proportions

The study area vulnerability proportions for both mapping approaches are summarized in Table 9.

4.9 Vulnerability Distribution by Local Government Area (LGA)

To provide localized insights for groundwater management, the spatial distribution of the vulnerability classes was delineated across the four LGAs (shown in Table 10). The data indicates a distinct spatial trend. Itu LGA exhibits the highest susceptibility, with 77.6% of its landmass classified as moderately vulnerable. In contrast, Ikono and Ini LGAs demonstrate high natural protection, with 85.2% and 78.1% of their areas, respectively, falling into the low vulnerability category.

4.10 Relationship Between Vulnerability and Groundwater Occurrence (G)

Groundwater Occurrence (G) serves as the primary driver of aquifer susceptibility in the hybrid framework, commanding a 65.67% effective weight in Single-Parameter Sensitivity Analysis.

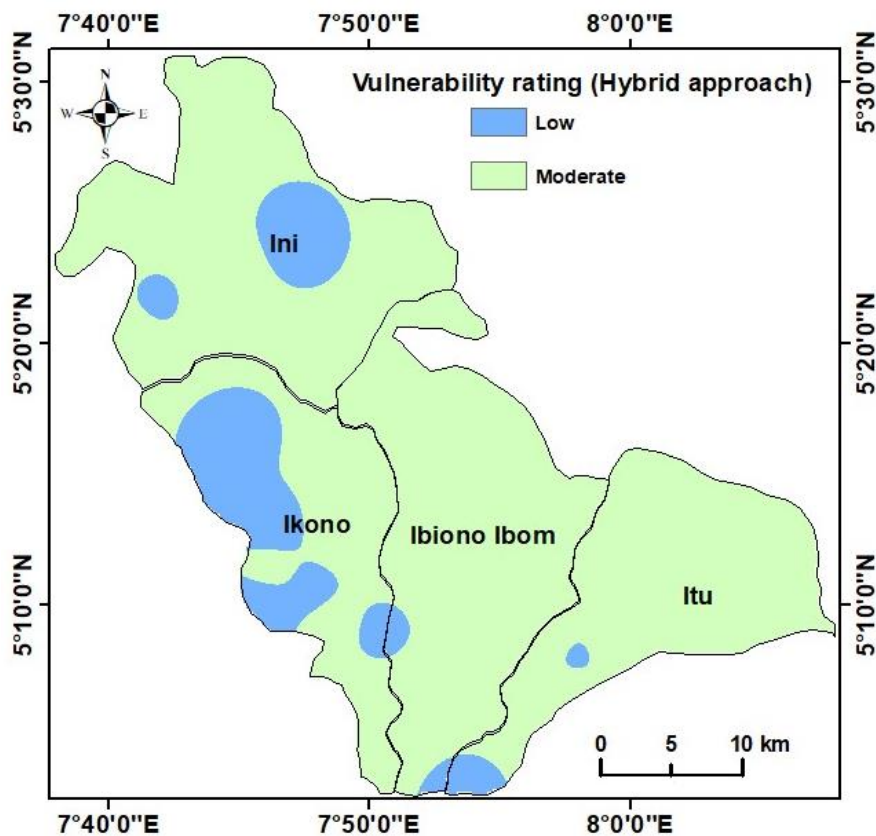


Figure 8: Hybrid GOD Index Map

Table 9: Percentage Vulnerability Coverage for both Approaches

Model Framework	Vulnerability Class	Percentage Area Coverage (%)	Structural Profile
Traditional GOD	Very Low / Negligible	~5	Isolated, fragmented circular pockets
	Low	~95	Dominant homogeneous regional background
Hybrid GOD	Low	30	Contiguous protective enclaves in Ini and Ikono
	Moderate	70	Regional unconfined/semi-confined baseline

Unconfined to Semi-Confined Conditions ($G = 0.6$) formed a baseline rating across the regional sands of the Benin Formation yielding consistent Moderate vulnerability scores due to direct surface exposure.

Confined / Artesian Conditions ($G = 0.2-0.3$) was capped by continuous, impermeable clay-shale beds (example Imo Shale) causing an immediate drop in vulnerability, isolating naturally protected Low vulnerability enclaves regardless of secondary parameter inputs.

Table 10: Percentage Distribution of Vulnerability Classes by LGA from Hybrid Approach

LGA	Area (%)	Low (%)	Moderate (%)
Itu	22.2	22.4	77.6
Ibiono Ibom	29.8	64.5	35.5
Ikono	26.2	85.2	14.8
Ini	21.8	78.1	21.9

4.11 Relationship Between Vulnerability and Depth to Water Table (D)

There is a direct inverse correlation between groundwater depth and vulnerability. Depth to Water Table (D) functions as a stabilizing background baseline parameter, contributing an 11.90% realized effective weight with a low standard deviation of 2.31% in map removal sensitivity.

Water table depths across the regional soundings fall within a relatively uniform depth band, yielding narrow D-ratings between 0.4 and 0.5 (corresponding to depth ranges of 10–50 m). Because water table depths remain stable across the regional landscape, parameter D anchors the continuous background matrix without distorting localized vulnerability boundaries. Where the water table exceeds 30 m in depth (such as in northern Ikono), the increased travel time provides a natural buffer, effectively holding the index in the Low vulnerability range.

4.12 Relationship Between Vulnerability and Overlying Lithology (O) Thickness

In areas like Ikono and Ini, the dominant overlying layers are characterized by thick, continuous sequences of clays and shaly-sands (interpreted from low deep borehole constrained VES resistivity values of 20–85 Ωm). These impermeable units yield low O-ratings (0.4), actively retarding the downward migration of contaminants and resulting in the dominant Low vulnerability classification. Conversely, the Moderate vulnerability zones in Itu are strongly correlated with highly porous, sandy lateritic topsoils, which offer minimal attenuation of surface pollutants. This Overlying Strata Lithology, acts as a secondary localized risk regulator (realized effective weight of 22.43%). The analysis indicates a decrease in vulnerability with increasing protective-layer thickness. Regions with an overlying protective thickness greater than 15 meters consistently yielded a GOD index below 0.25 (Low vulnerability).

However, where the protective thickness thinned to less than 5 meters, even if composed of clayey materials, the vulnerability sharply transitioned to Moderate, indicating that thickness plays an important role alongside lithological composition in shielding the aquifer matrix.

4.13 Sensitivity Analysis of the hybrid GOD index

4.13.1 Map Removal Method

The statistical outputs derived from the 30 VES stations are summarized in Table 11. From Table 11, the removal of parameter G triggers the largest structural disruption in the model, yielding an overall Mean Sensitivity of 20.54 % and Standard Deviation of 22.46 %. The sensitivity values span a wide range, from a minimum of 4.80% up to a maximum of 77.51%. These metrics reveal that the Hybrid GOD index is highly sensitive to the presence of the confinement layer. The high standard deviation confirms that this sensitivity is highly variable across the study area. In zones where thick clay layers create a confined or semi-confined aquifer, removing G completely alters the local risk profile, causing sensitivity to spike toward the 77.51% maximum. This suggest that G is the primary parameter responsible for defining the low-vulnerability protection zones.

The overlying lithology layer demonstrates a moderate Mean Sensitivity of 5.16%, with a maximum localized shift of 18.18% and a standard deviation of 6.86%. This profile indicates that while the vadose zone's lithology does not rewrite the entire vulnerability map, it serves as an important localized risk regulator. The 18.18% maximum sensitivity matches specific locations where the protective confinement layer weakens, allowing porous sand lenses to interact directly with the surface. Removing O in these areas hides these high-risk pathways, confirming that this parameter is essential for capturing localized contamination risks.

Table 11: Map removal sensitivity analysis result for Hybrid GOD index

Removed Parameter Layer	Minimum Sensitivity (%)	Maximum Sensitivity (%)	Mean Sensitivity (%)	Standard Deviation (%)
G (Groundwater Confinement)	4.80	77.51	20.54	22.46
O (Overlying Strata Lithology)	0.47	18.18	5.16	6.86
D (Depth to Water Table)	0.54	13.85	3.38	2.31

The Depth (D) parameter exhibits the lowest Mean Sensitivity (3.38%) and Standard Deviation (2.31%), with a maximum index shift of only 13.85%. This minimal change indicates that the Depth parameter acts as a stable architectural baseline for the model. Because the water table depth is relatively uniform across the regional landscape, removing it does not cause major shifts in the final vulnerability zones. Instead, it serves as a reliable baseline index value that anchors the regional calculations without distorting local boundaries. These MRSA results indicate that the optimized Hybrid GOD model is mathematically consistent and shows comparatively greater sensitivity. In an ideal model, no single parameter should have a mean sensitivity of 0% (which would mean it does nothing) or close to 100% (which would mean it operates completely alone). The clear hierarchy ($G > O > D$) confirms that each layer contributes a distinct type of spatial information to the final maps. This analysis provides environmental planners with a clear priority list for data collection. Because the model is highly sensitive to Groundwater Confinement (G) and Lithology (O), field monitoring budgets should prioritize high-resolution borehole logging and geophysical surveys to map these subsurface layers accurately. Conversely, because water table depth (D) is consistent, it can be updated less frequently without affecting the structural accuracy of the vulnerability zoning.

4.13.2 Single parameter sensitivity analysis

The summary of this analytical comparison is presented in Table 12. The SPSA confirms that

Groundwater Confinement (G) operates as the primary control mechanism over the risk profile in the study area, maintaining a massive mean effective weight of 65.67% (Table 10). Although this represents a minor drop (-3.63%) from its high theoretical assignment of 69.30%, its dominance explains why the final vulnerability map is divided into its current spatial configuration. Wherever the confinement layer remains at its standard baseline rating of 0.6 (indicative of semi-confined or leaky aquifer conditions), the overall index remains firmly within the Moderate risk zone. However, when local geological formations shift - dropping the raw G score down to 0.2 or 0.3 due to thick, impermeable clay capping or tight artesian confinement, the overall vulnerability index drops dramatically. Because the model is highly sensitive to parameter G, these localized shifts instantly override variations in other layers, producing the isolated low-vulnerability islands mapped out across central Ini and western Ikono LGAs.

A highly notable outcome of the sensitivity analysis is the significant upward shift observed in the Overlying Strata Lithology (O) parameter. Its real-world impact climbs by +4.22%, rising from a theoretical design weight of 18.21% up to an effective average of 22.43%. This systematic expansion suggests that local shifts in the overlying layer media act as an active risk amplifier within the study area (George et al., 2021). At specific sounding locations where the overlying lithology index peaks at 0.7 or 0.8 (denoting highly permeable sand channels, fractured sandstone, or porous alluvial deposits),

the layer aggressively increases the vulnerability calculation. This elevation makes Layer O the critical secondary diagnostic parameter for environmental managers, as it flags vulnerable

areas where porous vadose zones provide a direct pathway for surface pollutants to migrate downward into the water table.

Table 12: Statistical Comparison of Theoretical and Realized Effective Weights

Parameter Identifier	Theoretical Model Weight (P_i)	Realized Mean Effective Weight (W_i)	Empirical Model Role and Influence
G (Groundwater Confinement)	69.30%	65.67%	Primary Vulnerability Driver; controls the generation of the low-risk spatial pockets.
O (Overlying Strata Lithology)	18.21%	22.43%	Secondary Regulator; provides local amplification of risk indices where lithology becomes porous.
D (Depth to Water Table)	12.50%	11.90%	Stabilizing Background Parameter; maintains the uniform matrix layout across the study area.

In contrast to the dynamic shifts seen in the other layers, the Depth to Water Table (D) parameter displays exceptional numerical stability. It drops by a minor -0.61%, moving from a theoretical framework setting of 12.50% down to a mean effective weight of 11.89%. This minimal deviation highlights that water table depth functions as a consistent background indicator across Ini, Ikono, Ibiono Ibom, and Itu LGAs. Because the raw field values for layer D cluster tightly within a narrow range (predominantly alternating between 0.4 and 0.5, the parameter does not introduce erratic spatial patterns. Instead, it provides a stable baseline that anchors the extensive, contiguous Moderate vulnerability matrix observed across the regional landscape.

From a groundwater governance perspective, executing the SPSA validates the structural integrity of the hybrid machine-learning model. It demonstrates that the final vulnerability map is not merely mathematical artifacts of an abstract weighting matrix, but are deeply linked to actual field conditions. By proving that aquifer confinement (G) controls 65.67% of the model's behavior while lithology changes (O)

act as local risk amplifiers, this analysis provides environmental planning agencies with direct operational insights. Protection strategies can be customized: strict conservation and drilling regulations should target areas where the protective confinement layer thinned out (the Moderate matrix), while regions with high-confinement clay shields (the Low vulnerability zones) can be recognized as naturally protected hydrogeological sanctuaries.

In summary, the comprehensive sensitivity analysis validates the Hybrid GOD model as a consistent, efficient, and parsimonious framework for regional groundwater vulnerability mapping. By integrating Single-Parameter Sensitivity Analysis (SPSA) and Map Removal Sensitivity Analysis (MRSA), the research provides empirical proof that every included parameter serves a distinct, functional purpose without generating data redundancy. This validation confirms that compressing the mapping framework into three highly sensitive, subsurface indicators eliminates statistical noise and index padding, ensuring a streamlined and mathematically sound model structure (Udosen et al., 2024d, e, Umoh et al., 2025).

4.14 Comparative Analysis of Traditional versus Hybrid GOD Vulnerability Mapping

The spatial divergence observed between the conventional GOD vulnerability rating map (Figure 6) and that of the Hybrid Approach (Figure 8) underscores the limitations of relying solely on subjective criteria weighting. The conventional approach yields a homogeneous 'Low' vulnerability matrix, artificially compressed by uncalibrated parameter indexing. Conversely, the Hybrid Approach captures the multi-dimensional variance of the hydrogeological inputs by balancing AHP-derived expert weights with data-driven Entropy normalization and K-means zonation.

This dual-calibration prevents over-smoothing and unmasks a higher baseline risk ('Moderate') across Ibiono Ibom and Itu, while simultaneously carving out statistically sound, contiguous protection zones ('Low') in Ini and Ikono. Consequently, the Hybrid Approach mitigates the risk of type-II errors in groundwater resource protection planning, providing a more conservative and scientifically rigorous foundation for environmental policy and land-use zoning." A Type-II error (also known as a false negative) occurs when a model or monitoring framework concludes that an area is safe or has low vulnerability, when in reality, it is highly vulnerable to contamination.

4.15 Hydrogeological Implications and Literature Comparison

The findings of this study complement previous regional hydrogeological investigations in the Niger Delta Basin:

Comparison with Regional Studies: Earlier groundwater assessments in Akwa Ibom State (e.g., Ekanem, 2022; Udosen et al., 2023; Ekanem et al., 2024 a, b, c) identified high intrinsic susceptibility within the unconfined Coastal Plain Sands (Benin Formation). The moderate-to-high vulnerability mapped across Itu LGA (77.6% Moderate) aligns with these prior observations.

Methodological Synthesis: Studies utilizing standard parametric overlay models (e.g., Uche et al., 2021; Chukwuma et al., 2023) often reported spatial over-smoothing over broad sedimentary areas. Combining AHP–Entropy weighting with K-means classification addresses threshold-assignment subjectivity, yielding clear spatial delineation between the unconfined sands of Itu and the clay-shielded formations of Ini and Ikono. Linear spatial overlays in previous coastal assessments generated false negatives (Ekanem, 2022). The proposed framework confirms its structural findings through Single-Parameter and Map Removal Sensitivity Analyses, verifying that Overlying Strata Lithology acts as a secondary risk amplifier and ensuring the model remains mathematically stable (Ukwuani et al., 2024).

Methodological Considerations: While internal clustering validation metrics ($S = 0.93$) indicates a clear separation within the calculated VI distribution, these metrics evaluate model structure rather than observed chemical contamination. Future research incorporating systematic water quality sampling (e.g., nitrate, heavy metals) and solute transport modeling will provide helpful ground-truth validation of the delineated risk zones.

5.0 Conclusion

This study developed an integrated hydrogeophysical framework combining 1D VES, 2D ERT, borehole logs, AHP–Entropy weighting, and K-means clustering to map groundwater vulnerability across northeastern Akwa Ibom State, Nigeria. The principal findings include:

1. **Hydrogeophysical Stratigraphy:** Inverted geoelectric profiles constrained with deep borehole lithology, resolved a 3-to-5-layer subsurface sequence, distinguishing highly permeable, unconfined coarse sands (1,053.1 - 3,070.7 Ωm) within the Benin Formation in Itu from low-resistivity clay aquitards (45.8 - 94.5 7 Ωm) associated with the Imo Shale and Ameki formations in Ini and Ikono.

2. Hybrid Weighting: Linear synthesis of expert-driven AHP weights and objective Information Entropy weights established unified parameter weights: G = 69.30%, O = 18.21%, and D = 12.50%.

3. Data-Driven Zonation: K-means clustering (k=2) applied to the continuous VI raster partitioned the study area into Moderate (70% area coverage; 21 VES stations) and Low (30% area coverage; 9 VES stations) vulnerability zones. Internal cluster metrics (S = 0.93, DBI = 0.14, CHI = 791.50) confirmed clear internal separation of the model-derived index classes. In contrast, the conventional GOD model categorized approximately 95% of the region as Low vulnerability, producing a substantially more homogeneous mapping pattern.

4. Parameter Sensitivity: Single-Parameter Sensitivity Analysis confirmed Groundwater Confinement (G) as the primary vulnerability control (65.67% effective weight), while Overlying Strata Lithology (O) functions as a secondary localized regulator (22.43% effective weight).

These results offer useful spatial insights for regional groundwater management. Environmental planning authorities can utilize these maps to prioritize hydrogeological field monitoring, establish protective buffer zones around high-yield wellfields in permeable sand formations, and guide land-use planning across northeastern Akwa Ibom State.

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