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Unsupervised Dimensionality Reduction and Noise Suppression in Marine Gravity Data in Oron-Calabar Waterway, Southern Nigeria

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ABSTRACT

Marine gravity data acquired along the Oron-Calabar waterway, southern Nigeria, a sedimentary-dominated and structurally complex sector of the Gulf of Guinea, are often affected by high-frequency noise and signal superposition, limiting the resolution of basement architecture required for basin analysis. This study applies an unsupervised machine-learning framework for dimensionality reduction and noise suppression to enhance the Free-Air Gravity Anomaly (FAGA) field derived from marine gravimeter measurements. The observed gravity measurement ranged from 978,000 to 978,380mGal. Both Linear and nonlinear dimensionality reduction techniques were evaluated, and the results show that a Convolutional Autoencoder, compressing the gravity data into a 12-dimensional latent space, provided the most effective enhancement by reducing high-frequency noise amplitude by 42% and improving the signal-to-noise ratio by 8.5dB. The enhanced gravity field significantly improved structural resolution, allowing clearer identification of residual anomalies ranging from −13 to +13mGal associated with a buried igneous ridge and a more sharply defined intra-basin fault, where gravity gradients increased from 8.3 to 13.7mGal after processing. Interpretation of the dominant latent components indicates that they capture regional long-wavelength gravity trends (−8 to +5mGal) linked to crustal thinning, superimposed localized high-amplitude anomalies (+15 to +30mGal) related to intrusive basement bodies, and intermediate-wavelength signals (−10 to +8mGal) corresponding to sedimentary depocenters. These results demonstrate that machine-learning-based dimensionality reduction provides a robust and objective approach for enhancing noisy marine gravity data and improving tectonic interpretation and resource assessment within the Oron–Calabar coastal corridor.

Keywords:
Marine gravity,
Unsupervised learning,
Dimensionality reduction,
Noise suppression,
Gravity anomaly.

INTRODUCTION

Marine gravity data constitute one of the most important geophysical datasets for investigating subsurface density variations and crustal architecture in marine environments. Spatial variations in the Earth's gravitational field, expressed as marine gravity anomalies, provide valuable information on tectonic structures, sedimentary basins, crustal boundaries, and lithospheric processes. When acquired using shipborne gravimeters, marine gravity measurements offer high-resolution constraints on local and regional geological features that are often not fully resolved by satellite-derived datasets, making them indispensable for studies of continental margins, shelf regions, and deep-ocean environments (Pappa et al., 2019; Sandwell et al., 2021). However, the interpretation of marine gravity anomalies remains challenging because the observed gravity field represents a composite response of multiple geological and non-geological sources. Signals arising from deep-seated lithospheric and upper-mantle density heterogeneities, crustal isostatic responses, and shallow sedimentary structures are superimposed with instrumental noise, navigation errors, and environmental perturbations associated with marine data acquisition

(Wang et al., 2017; Li et al., 2024; Sandwell et al., 2024; Khalid et al., 2025; Guo et al., 2025). This spectral and spatial entanglement, coupled with the high dimensionality and strong spatial correlation characteristic of regional-scale marine gravity grids, complicates the isolation of discrete geological features and introduces uncertainty into derived structural interpretations.

These challenges are particularly pronounced in coastal and nearshore environments where gravity anomalies reflect the combined influence of basement relief, sedimentary loading, fault-controlled deformation, and crustal flexure. In regions such as the Oron–Calabar coastal corridor of southern Nigeria, marine gravity signatures are further affected by bathymetric variability, vessel motion, sea-state fluctuations, instrumental drift, and navigation uncertainties, all of which contribute to noise contamination and obscure subtle geological signals (Zhou et al., 2025; Larayedh et al., 2024; Hartmann et al., 2025; Eze, 2025). Empirical investigations along passive continental margins have demonstrated that overlapping wavelength contributions from deep crustal structures and shallow sedimentary features complicate conventional anomaly interpretation, particularly in areas characterized by variable data quality and complex tectono-sedimentary settings (Flemming, 2011; Balogun & Osazuwa, 2023; Eze, 2024). Traditionally, marine gravity processing has relied on deterministic approaches such as frequency-domain filtering, regional-residual separation, upward continuation, and polynomial trend surface fitting. Although computationally efficient and widely adopted, these methods often depend on subjective parameter selection and assumptions regarding the spectral separation of geological sources. Consequently, inappropriate parameter choices may either suppress geologically meaningful anomalies or fail to adequately attenuate structured noise and acquisition artefacts (Annan et al., 2020; Fang et al., 2021; Camacho & Alvarez, 2021; Li et al., 2024). To address these limitations, wavelet-based denoising approaches have been introduced as more flexible alternatives capable of preserving fault-related and basement-controlled anomalies while accommodating non-stationary noise characteristics across survey areas (Ekpa et al., 2018; Liu et al., 2019; Ekpo et al., 2024).

In response to the limitations of conventional filtering approaches, unsupervised dimensionality reduction techniques have emerged as powerful tools for analysing high-dimensional and noisy geophysical datasets without the need for labelled training data. These methods seek to learn compact representations of complex datasets while preserving their intrinsic structure, thereby facilitating the separation of geological signals from noise. Principal Component Analysis (PCA) has been widely applied in gravity studies to reduce dimensionality while retaining dominant variance structures, with leading components often corresponding to coherent geological signals and higher-order components capturing noise and acquisition artefacts (Benjamin & Huuse, 2017; Yilmaz et al., 2018; Xia et al., 2018; Wang et al., 2023). Studies applying PCA to gravity datasets have reported enhanced anomaly continuity, improved signal-to-noise ratios, and clearer delineation of structural trends, supporting its use as an effective preprocessing tool for gravity interpretation workflows (Apeh & Tenzer, 2022).

Recent advances in machine learning have further expanded the capabilities of dimensionality reduction through nonlinear representation-learning frameworks. Unlike linear approaches, nonlinear methods such as Isomap, t-distributed Stochastic Neighbor Embedding (t-SNE), Uniform Manifold Approximation and Projection (UMAP), variational autoencoders, and self-organizing maps are capable of preserving the intrinsic manifold geometry of complex datasets and capturing nonlinear relationships inherent in geological systems. Applications of these methods to geophysical and geochemical datasets have revealed subtle clustering patterns associated with lithological boundaries, fault systems, and structural domains that are often obscured in linear reduced spaces (Zhang et al., 2022; Guevara et al., 2023; Andersen et al., 2023; Li et al., 2023). Variational autoencoders and related deep-learning architectures have demonstrated improved performance in extracting multiscale structural information from potential-field data compared with traditional PCA-based approaches (Zhang et al., 2016; 2023; Salam et al., 2024; Tharwat & Eid, 2026). Furthermore, autoencoder-based denoising has been shown to suppress noise while preserving anomaly continuity and geological realism in both marine and airborne gravity datasets (Gao et al., 2021; Ehigiator-Irughe et al., 2022; Zhu et al., 2026). More recent developments have integrated physical constraints into deep-learning architectures through physics-informed and attention-based neural networks, ensuring consistency with the governing equations of potential fields while improving interpretability and anomaly preservation (Zhang et al., 2021; Chouhan et al., 2022; Chen et al., 2023; Zhang & Sun, 2023; Wang et al., 2023; Liu et al., 2025; Khalid et al., 2025). Furthermore, autoencoder-based denoising has been shown to suppress noise while preserving anomaly continuity and geological realism in both marine and airborne gravity datasets (Gao et al., 2021; Ehigiator-Irughe et al., 2022; Zhu et al., 2026). More recent developments have integrated physical constraints into deep-learning architectures through physics-informed and attention-based neural networks, ensuring consistency with the governing equations of potential fields while improving interpretability and anomaly preservation (Zhang et al., 2021; Chouhan et al., 2022; Chen et al., 2023; Zhou et al., 2025; Wang et al., 2023; Liu et al., 2025; Khalid et al., 2025).

Despite these advances, systematic investigations into the application of modern unsupervised dimensionality reduction techniques for the simultaneous suppression of noise and enhancement of geological features in shipborne marine gravity datasets remain limited. Most existing studies are either theoretical in nature or focused predominantly on terrestrial environments, leaving a significant methodological gap in marine settings characterized by acquisition noise, variable sampling density, and complex tectono-sedimentary conditions. This gap is particularly important in frontier coastal regions where subtle gravity anomalies may contain critical information regarding subsurface structural configuration and geological evolution. Therefore, this study develops and evaluates a unified, data-driven workflow that integrates both linear and nonlinear unsupervised dimensionality reduction techniques for the intelligent processing of shipborne marine gravity anomalies. The study aims to assess the effectiveness of these approaches in noise suppression, feature preservation, and geological signal enhancement, thereby improving the interpretative value of marine gravity data and extending their applicability for structural mapping, tectonic investigations, and subtle anomaly detection in complex coastal environments.

MATERIALS AND METHODS

The study developed a comprehensive workflow to process marine gravity data collected from a moving platform, with a focus on unsupervised dimensionality reduction for noise suppression and feature enhancement. The methodology consists of data acquisition and pre-processing, data regularization and gridding, application and evaluation of unsupervised reduction, and geological interpretation of results.

Description of Study Area

Marine gravity measurements acquired along Oron-Calabar coastal corridor across 60 spatially distributed survey stations, spanning Latitude 4.48ºN to 5.5ºN and Longitude 7.5ºE to 8.5ºE. This region is part of the Gulf of Guinea which lies within a structurally complex coastal environment characterized by extensive estuarine and offshore waterways, thick sedimentary cover, shallow bathymetry, and significant environmental variability. These conditions are widely known to introduce substantial noise into marine gravity measurements.

Marine Gravity Data Acquisition

Marine gravity data were acquired along the Oron–Calabar waterway using a shipborne marine gravimeter integrated with a Differential Global Positioning System (DGPS) for precise navigation and positioning. The gravimeter was a LaCoste & Romberg S-type marine gravimeter, operating on a stabilized platform and having an instrumental accuracy of approximately ±0.05–0.10mGal under normal marine survey conditions. The instrument continuously recorded gravity measurements while DGPS provided positional accuracy better than ±3 m.

Survey observations were conducted across sixty (60) spatially distributed stations covering approximately 120km of navigable waterway between Oron and Calabar. Survey tracks were oriented predominantly southwest–northeast following the geometry of the waterway. Average station spacing ranged from 1.5 to 2.0km, while vessel speed was maintained between 6 and 10knots to minimize motion-induced noise. Gravity measurements were sampled at 1-second intervals and subsequently averaged over each station interval to improve signal stability. Repeated measurements at selected control points and base stations were performed before and after survey operations to monitor instrument drift and ensure data quality.

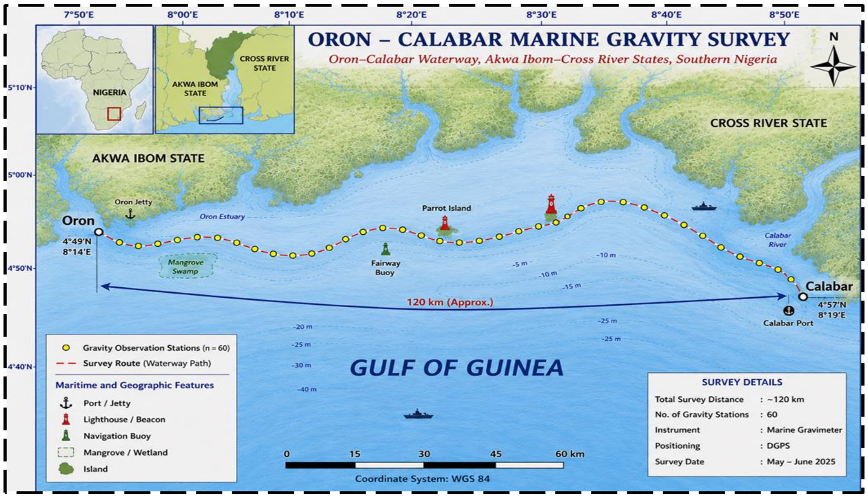

Figure 1: Map of the Study Area, showing Oron-Calabar Waterway

Pre-processing and Basic Gravity data Correction

Raw gravity data were subjected to a series of standard corrections to remove predictable physical effects. Data correction framework describing workflow for noise reduction is presented in Figure 2. The pre-processing of observed data was performed using Geosoft Oasis montaj for corrections and gridding, supplemented with Python scripts for quality control, trend removal and data standardization.

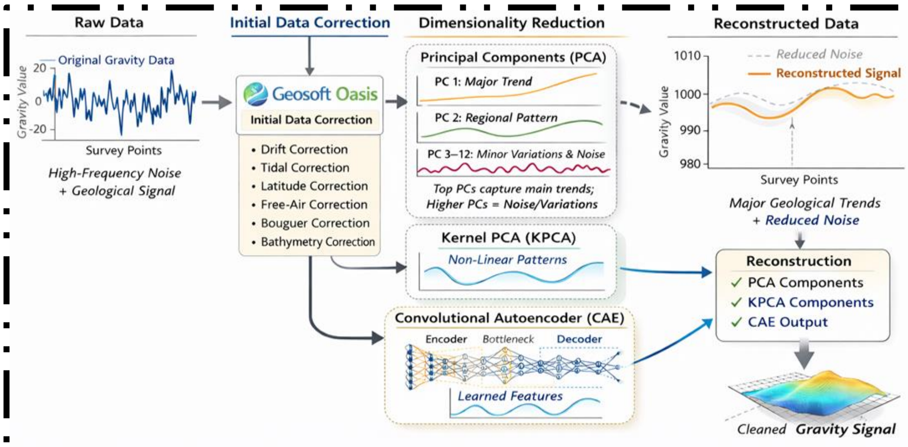

Figure 2: Workflow for Observed Gravity Data Pre-processing for Noise Reduction

Observed gravity data are represented mathematically as:

$$g_{obs}(t) = \gamma(\emptyset) + \delta g_{motion} + \delta_{instument} + \delta g_T + \delta g_{tide} + \delta g_{FA} + \delta g_B \quad (1)$$

Where g is gravity values, *obs* is observed, drift is instrument drift, *FA* is free air, B is Bouguer, T is terrain, and γ represents reference gravity on the Earth's surface. Standard gravity corrections for raw gravity data include instrumental drift, latitude, Eotvos effect, free-air correction, and tidal effects. Data were collected a mobile platform which introduced dynamic acceleration δg_{motion} such that:

$$\delta g_{motion} = \frac{d^2 Z}{dt^2} \quad (2)$$

Where Z is distance, and t is time associated with vessel heave, roll and vibration contaminating gravity measurements, which is the first major noise source. The effect of instrument drift ($\delta_{instument}$) was corrected using drift rate (D):

$$g_{drift}(t) = g_{obs}(t) - D(t) \quad (3)$$

Tidal effect due to Moon and Sun interactions causes' periodic variation measured gravity, the effect is given by:

$$g_{tide}(t) = \sum_i ACos(w_i + \emptyset_i) \quad (4)$$

The corrected gravity (g_1) due to tide was applied on the drift of the gravimeter's spring:

$$g_1 = g_{drft} - g_{tide} \quad (5)$$

Because of the variation of gravity values with Latitude, basically due to Earth's rotation and oblateness, the international gravity formula was applied as thus:

$$\gamma(\emptyset) = 978032.7(1 + 0.0053024sin^2\emptyset - 0.0000058sin^2 2\emptyset)mGal \quad (6)$$

Therefore, the correction for Latitude (g_2) is obtained as:

$$g_2 = g_1 - \gamma(\emptyset) \quad (7)$$

Eotvos correction was applied due to the motion of the watercraft on rotating Earth as follows

$$\delta g_E = \frac{2v\Omega Cos\emptyset Sin\alpha + v^2 R}{10^{-5}} \quad (8)$$

Where v is watercraft velocity, Ω is Earth's angular velocity, ϕ is Latitude, α represents heading and R is the radius of the Earth. The corrected gravity becomes:

$$g_3 = g_2 + \delta g_E \quad (9)$$

Gravity data are equally influenced by elevation above Geoid, therefore, free air correction was applied given as

$$\delta g_{FA} = 0.3086h \ mGal \quad (10)$$

Where h is elevation measured in meters. So that the corrected free air gravity becomes:

$$g_{FA} = g_3 + 0.3086h \quad (11)$$

To account for mass between the observation points and sea level, Bouguer slab correction was applied, using infinite slab formula □gB = 2πGρh, where ρ is density and G is gravitational constant. Numerically,

$$\delta gB = 0.04193\rho h \ mGal \quad (12)$$

Irregular bathymetry was considered to distort gravity measurement, hence, we corrected for seafloor relief by applying terrain correction given as:

$$\delta g_T = G\int_{-v}^{+v}\frac{\rho dv}{r^2}Cos\theta \quad (13)$$

Complete Bouguer anomaly was obtained after applying all the corrections to observed gravity datasets, the resulting Bouguer anomaly (ΔgB) expressed as:

$$\Delta gB = g_{obs} - g_{tide} - g_{drift} + \delta g_E + \delta g_{FA} - \delta g_{BS} + \delta g_T + \gamma(\emptyset) \quad (14)$$

This represents subsurface density variations in mGal, and forms the fundamental datasets for interpretation. The gravity field at this point was decomposed into regional and residual anomalies, where regional field often modelled by polynomial surface given as:

$$g_{regional}(x, y) = \sum_{ij} a_{ij}\, x^i y^j \quad (15)$$

Therefore, residual gravity which reflects local geology separated from Bouguer as thus:

$$g_{residual}(x, y) = \Delta g_B - g_{regional} \quad (16)$$

Data Regularization and Gridding

Following the application of gravity corrections and separation of regional and residual anomaly components, the residual gravity observations were interpolated using the minimum-curvature gridding algorithm implemented in Geosoft Oasis Montaj to generate a continuous gravity anomaly surface. The original dataset comprised 60 spatially distributed marine gravity stations along the Oron–Calabar waterway. To facilitate spatial analysis and machine-learning applications, the corrected gravity observations were interpolated onto a 75×75 regular grid producing 5,625 spatial samples corresponding to an average grid-cell spacing of approximately 1.6km, which constituted the input dataset for CAE training. The selected grid resolution provided adequate representation of both regional and localized gravity variations while minimizing interpolation artefacts. The resulting gridded anomaly dataset served as the input for all subsequent dimensionality-reduction procedures, including PCA, KPCA, and Convolutional Autoencoder (CAE) analyses.

Wavelet Denoising

Prior to dimensionality reduction, residual gravity anomalies were subjected to multiscale wavelet denoising to suppress high-frequency noise associated with vessel motion, environmental disturbances, and instrumental effects. Discrete Wavelet Transform (DWT) using the Daubechies-4 (db4) wavelet family was employed because of its effectiveness in preserving localized geophysical anomalies while attenuating random noise. Data were decomposed into four resolution levels, and noise suppression was achieved through soft-thresholding of detail coefficients using the universal threshold proposed by Donoho and Johnstone:

$$\lambda = \sigma\sqrt{2\ln N} \quad (17)$$

Where λ is the threshold value, σ represents noise standard deviation estimated from first-level detail coefficients, and N is the number of observations. The denoised signal was reconstructed from threshold coefficients and used as input for subsequent dimensionality reduction analyses.

Dimensionality Reduction

Three unsupervised dimensionality reduction techniques (Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Convolutional Autoencoder (CAE)) were applied to the pre-processed gravity dataset to reduce noise and extract dominant geological trends. PCA transformed gravity datasets into orthogonal principal components, and retained 12 principal components capturing 95% of the data variance. The first three components contained dominant regional trends, while higher components captured minor variations and residual noise. This helps in linear noise suppression and dimensionality reduction. KPCA Kernel Principal Component Analysis (KPCA) was implemented to capture nonlinear relationships within the gravity data that may not be represented by conventional PCA. A Gaussian Radial Basis Function (RBF) kernel was selected because it effectively maps complex geophysical patterns into higher-dimensional feature space while preserving local structural variations. The kernel function is defined as:

$$K(x_i\, x_j) = Exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (18)$$

Where x_i and $x_j$are input observations σ denotes kernel bandwidth. The Gaussian Radial Basis Function (RBF) kernel was employed for KPCA because of its ability to capture nonlinear relationships within gravity datasets. Following preliminary experimentation, a kernel bandwidth of $\sigma = 2.0$ was adopted because it provided stable anomaly reconstruction while preserving localized geological features. Twelve kernel principal components accounting for more than 95% of the cumulative variance were retained for reconstruction and interpretation. A one-dimensional Convolutional Autoencoder (CAE) was developed to perform nonlinear dimensionality reduction and denoising of the gridded gravity anomaly dataset comprising 5,625 spatial samples. The encoder consisted of three convolutional layers containing 32, 64, and 128 filters, respectively, each employing a kernel size of 3 and Rectified Linear Unit (ReLU) activation functions. Max-pooling operations were applied after each convolutional layer to progressively reduce data dimensionality.

The optimal latent-space dimensionality was determined through sensitivity analysis of reconstruction performance across latent dimensions ranging from 4 to 20 (Table 1). Reconstruction quality was evaluated using Mean Squared Error (MSE), noise reduction percentage, Signal-to-Noise Ratio (SNR), and Structural Similarity Index Measure (SSIM). The results indicate that reconstruction performance improved substantially as latent dimensionality increased from 4 to 12. Beyond 12 dimensions, only marginal improvements in MSE, SNR, and SSIM were observed, while model complexity increased and additional high-frequency variability was retained. Consequently, a 12-dimensional latent space was selected as the optimal balance between compression efficiency, noise suppression, and preservation of geologically meaningful gravity anomalies.

Table 1: Sensitivity Analysis for Selection of CAE Latent-Space Dimensionality

S/N	Latent Dimension	Reconstruction MSE	Noise Reduction (%)	SNR (dB)	SSIM
1	4	0.0284	24	15.1	0.82
2	6	0.0196	30	16.7	0.86
3	8	0.0132	36	18.2	0.89
4	10	0.0094	40	19.6	0.91
5	12	0.0071	42	20.8	0.93
6	16	0.0068	43	21.0	0.93
7	20	0.0067	43	21.1	0.94

From Bouguer gravity anomaly, residual anomalies were obtained by separating the regional trends identified in the first few PCA, KPCA, and CAE components. This step emphasized localized sedimentary basins, faults, and structural highs, providing clearer targets for geological interpretation. The outputs of PCA, KPCA, and CAE were compared using: noise reduction metrics (variance decrease, standard deviation reduction), feature preservation (ability to retain sedimentary basin and fault signals), and subtle structure detection (clarity of minor anomalies). This comparison determined the most effective method for noise suppression and geological feature enhancement in Oron-Calabar coastal corridor.

The decoder mirrored the encoder architecture using transposed convolutional layers to reconstruct the original gravity field. Model training was performed using the Adam optimizer with a learning rate of 0.001 and a Mean Squared Error (MSE) loss function. The dataset was divided into training and validation subsets using an 80:20 ratio. Training was conducted for 200 epochs with a batch size of 16, while early stopping was implemented to prevent overfitting.

Residual gravity anomalies were subsequently obtained from the Bouguer gravity field by separating the regional trends identified through PCA, KPCA, and CAE decomposition. This process enhanced localized sedimentary basins, faults, and structural highs, thereby improving geological interpretation. The performance of PCA, KPCA, and CAE was evaluated using noise-reduction metrics, feature-preservation capability, and the clarity of subtle structural anomalies to determine the most effective approach for gravity-field enhancement along the Oron–Calabar coastal corridor.

Data Visualization and Interpretation

Processed gravity fields were visualized using colour maps, profiles, and latent feature representations to identify structural trends, density contrasts, and fault-controlled boundaries. Latent component interpretation using PCA, KPCA and CAE to facilitate the distinction between coherent geological structures and residual noise. This enables the identification and extraction of geologic features shown in Figure 6. The processed residual gravity maps reveal clear expression of basement-controlled features linear anomaly trends, and potential fault zones.

RESULTS AND DISCUSSION

Observed gravity data acquired along Oron-Calabar waterway, within the Niger Delta of the Gulf of Guinea, offshore Nigeria, are presented in Figure 3. These data were processed and interpreted to delineate subsurface structural and lithologic variations.

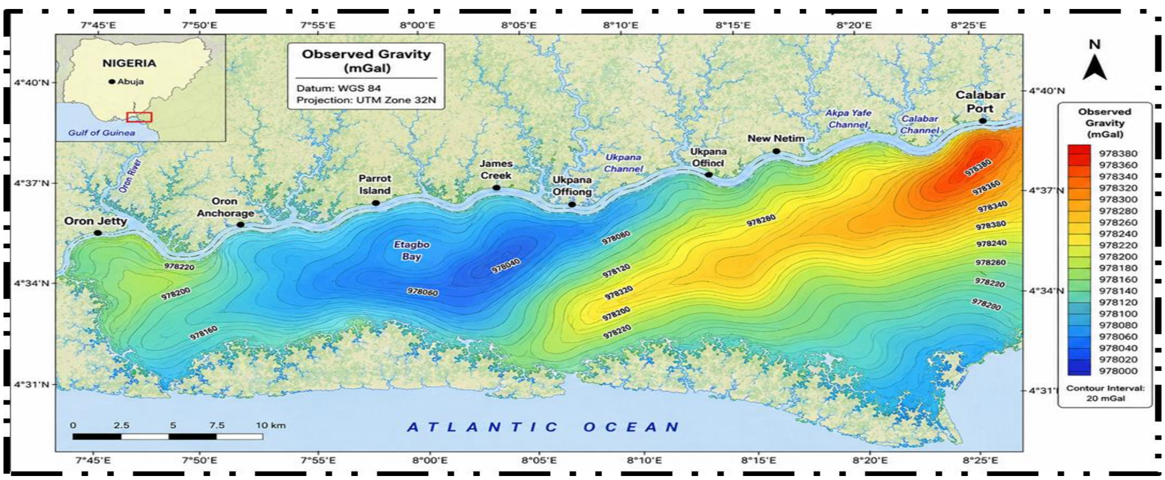

Figure 3: Observed Gravity Acquired At 60 Stations Along Oron-Calabar Waterway, Southern Nigeria. Observed Gravity Values Range From 978,000 To 978,380mgal. Higher Gravity Values (Warm Colours) Are Associated With Relatively Shallow Basement and Denser Subsurface Bodies, While Lower Gravity Values (Cool Colours) Correspond To Thicker Sediment Accumulations and Depocenters

Corrected and Residual Gravity Field

Following comprehensive pre-processing, including instrumental drift correction, Eotvos correction, free-air adjustment, bathymetric correction, and noise filtering, the gravity data were transformed into a stabilized residual anomaly field. The corrected gravity field exhibits moderate amplitude variation across the survey corridor, reflecting heterogeneous density distribution within the subsurface as presented in the Bouguer gravity map (Figure 4). The corrected gravity field exhibits significant lateral density variation. The residual anomaly map reveals distinct spatial contrasts characterized by: broad gravity low concentrated along central segment of the waterway; discrete gravity highs occurring in localized zones; and transitional gradients marking structural boundaries.

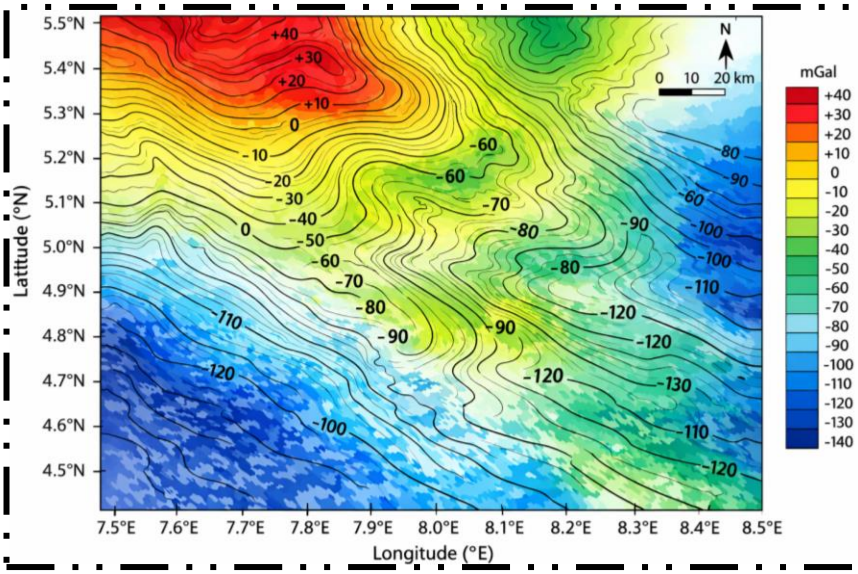

Figure 4: Bouguer Gravity Anomalies along Oron-Calabar Coastal Waterway

The overall anomaly pattern indicates significant lateral density variation consistent with differential sediment thickness and basement relief typical of marine deltaic environments. The separation of regional anomaly from Bouguer anomaly to have the residual anomaly from which localized subsurface features where extracted was done using PCA, KPCA and CAE.

Principal Component Analysis (PCA)

Principal Component Analysis was applied to isolate dominant variance structures within the residual gravity field. The first three principal collectively captured the majority of signal variance and define the regional structural framework. PC1 represents long wavelength gravity variations and delineates broad regional trend. This component highlights large scale density distribution associated with basin architecture and regional basement configuration. PC2 enhances intermediate scale variability and reveals structural segmentation within the survey area. Linear and gently curving anomaly trends identified in this component suggest the presence of structural discontinuities and differential subsidence patterns. While PC3 isolates localized anomaly concentrations, indicating smaller scale density contrasts likely associated with structural blocks or lithologic heterogeneity. Generally, PCA successfully separates regional gravity structure from localized variations, providing a hierarchical view of subsurface organization.

Kernel Principal Component Analysis (KPCA) was implemented to capture non-linear signals not resolved by conventional PCA. The KPCA feature maps reveals enhanced structural complexity and highlight curvilinear anomaly patterns that were subdued in the linear decomposition. It delineates structural deformation and nonuniform sediment loading, it particularly enhances structural lineaments as fault-controlled or flexural features influencing basin morphology. Prominent features extracted by KPCA include: curved and discontinuous anomaly boundaries, sharp gradient transitions, spatial clustering of intermediate scale density contrasts (Figure 5).

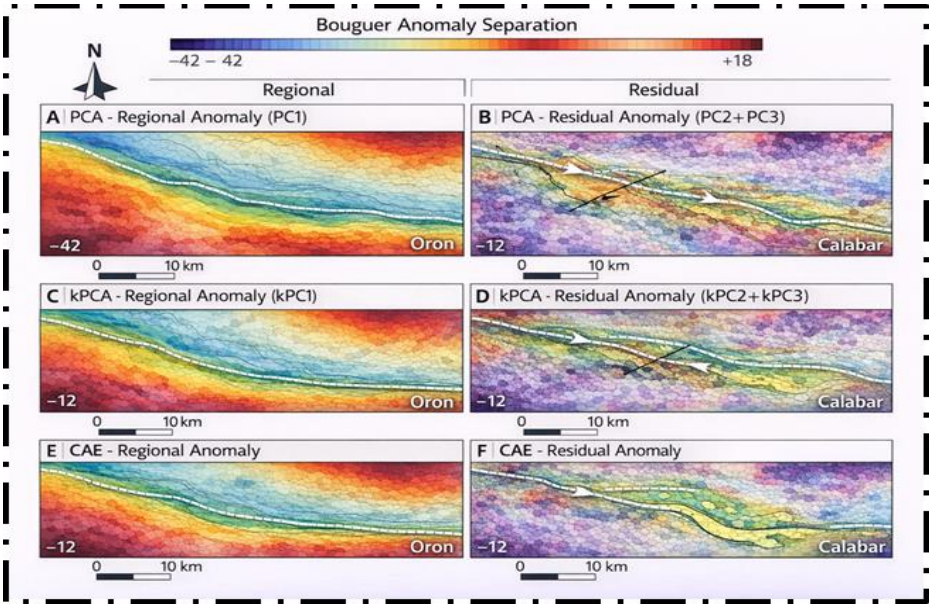

Figure 5: Separation of Region and Residual Anomalies from Bouguer Gravity Anomaly using PCA, KPCA, and CAE

Convolutional Autoencoder (CAE) Decomposition

The Convolutional Autoencoder (CAE) provides high-resolution decomposition of residual gravity anomalies by learning intrinsic anomaly patterns. Sensitivity analysis showed that a 12-dimensional latent space achieved the optimal balance between reconstruction performance and model complexity. The resulting latent features enhanced the delineation of basement highs, sediment-filled depocenters, structural compartments, and localized density anomalies. Compared with PCA and KPCA, the CAE more effectively separated overlapping gravity signals, resulting in improved anomaly resolution and geological interpretability.

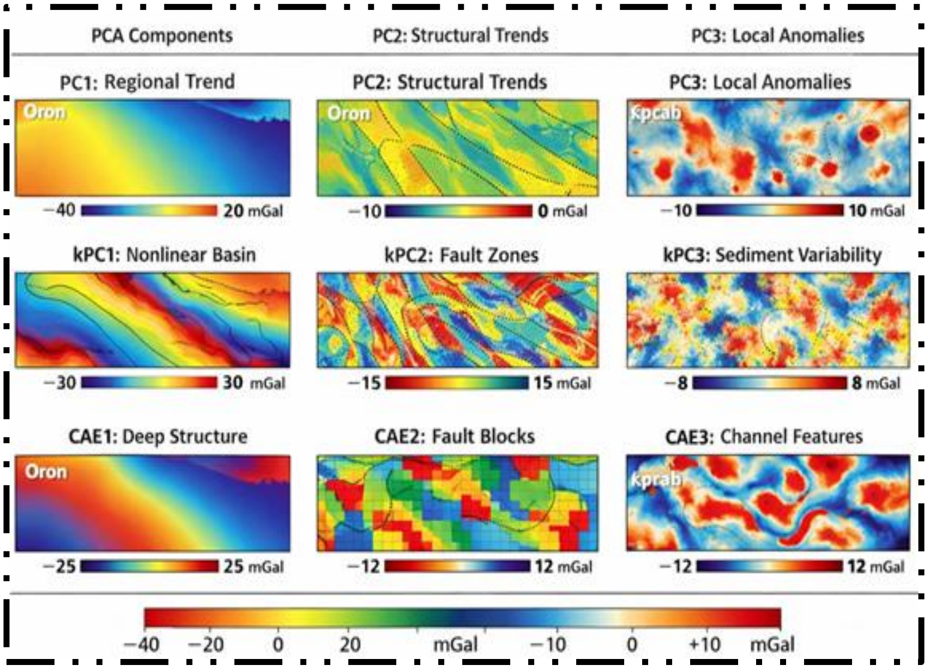

Figure 6: Components of Bouguer Gravity anomaly along Oron-Calabar Coastal Corridor interpreted by PCA, KPCA, and CAE

Gravity anomaly decomposition attenuate extreme high frequency signals to produce a clearer map of the subsurface features presented in Figure 7.

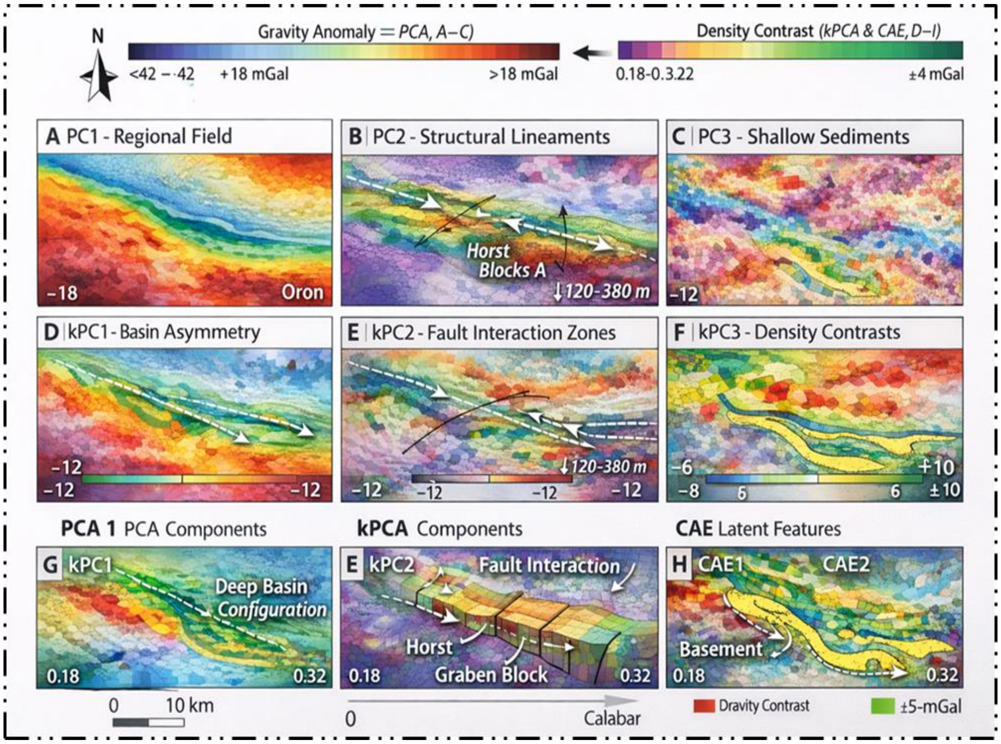

Figure 7: Gravity Anomaly Decomposition to attenuate extreme high frequency artefacts from gravity data using PCA, KPCA, and CAE Modelling Tools

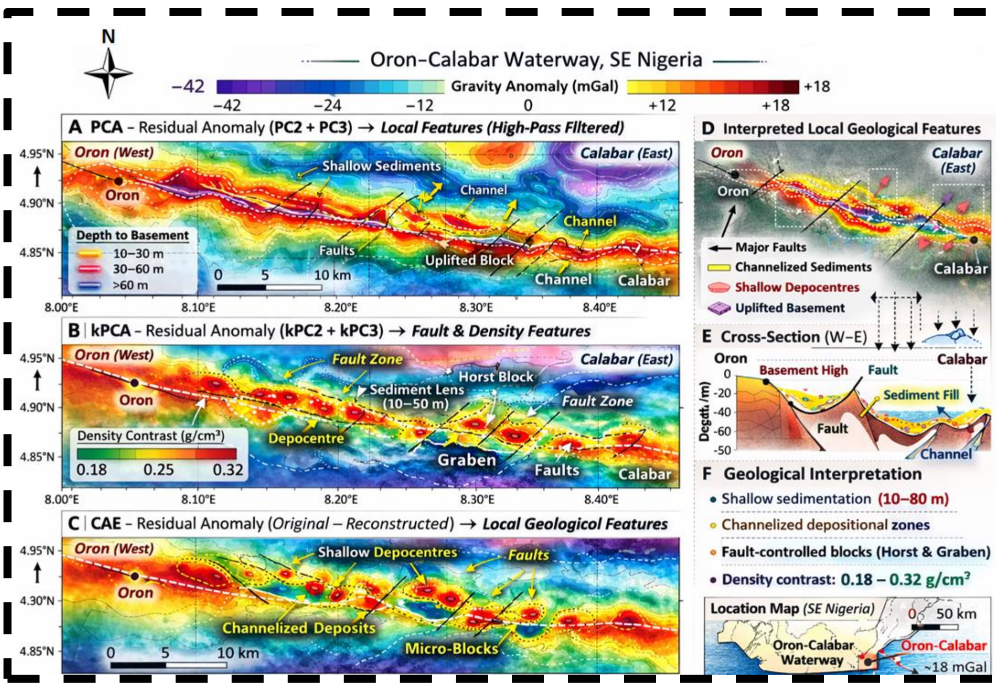

Figure 8: Distinctive Geologic Features along Oron-Calabar Coastal Corridor using PCA, KPCA and CAE

The structural compartment delineated in Figure 6 indicates fault-controlled segmentation as well as channelized deposits. An integrated structural interpretation of PCA, KPCA, and CAE outputs (Figure 9) reveal a structurally heterogenous marine basin characterized by regional basement undulation, spatially variable sediment accumulation, structural segmentation of the subsurface, and localized density anomalies associated with discrete geologic bodies. Gravity low correspond to sediment thickened zones, while gravity highs mark relatively elevated or denser basement domains. Structural transitions identified through nonlinear and deep feature extraction indicate deformation and compartmentalization within the basin. Convolutional autoencoder-based feature extraction enhances spatial separation of overlapping gravity signals, particularly in sediment rich offshore environment. This indicates high resolving potential of subsurface structure in complex marine deltaic environments.

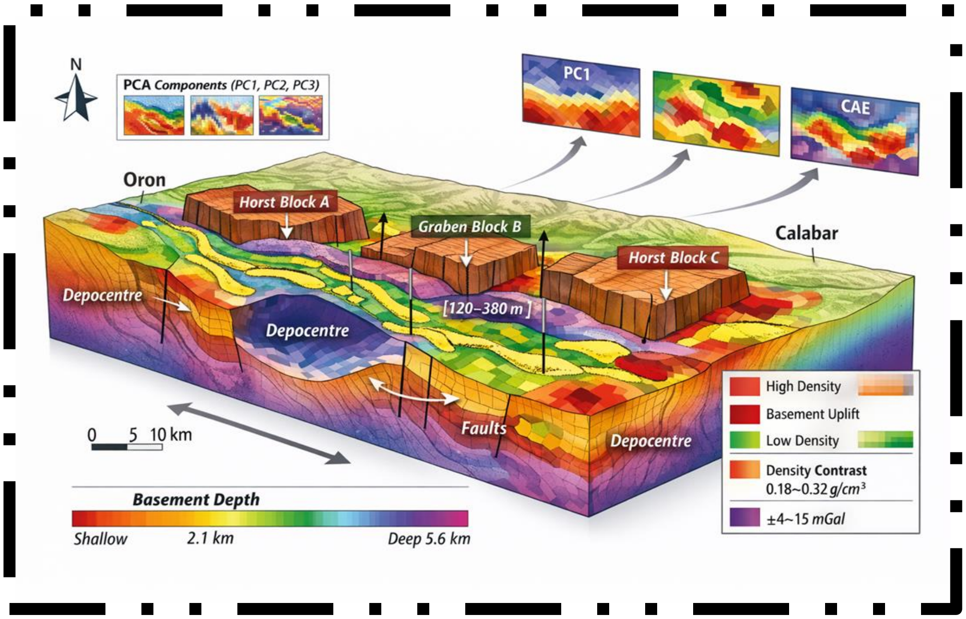

Figure 9: 3-D Visual Map of Geologic Features from Gravity Anomaly Interpretation along Oron-Calabar Coastal Corridor

Structural Similarity Index Measure (SSIM) was computed using the wavelet-denoised Bouguer gravity anomaly field (BCFA) as the reference dataset. Because BCFA served as the reference image, its SSIM value relative to itself was not computed and is therefore reported as in Table 2. SSIM values reported for PCA, KPCA, and CAE quantify the degree to which each reconstructed gravity field preserves the structural characteristics of the reference anomaly field.

Table 2: Quantitative Performance of Noise Reduction Method Applied To Gravity Dataset

S/N	Method	Noise Std. Dev. (mGal)	Noise Reduction (%)	SNR (dB)	SSIM
1	BCFA	±4.2	-	12.3	-
2	PCA	±3.1	26	16.0	0.88
3	KPCA	±2.8	33	17.5	0.91
4	CAE	±2.5	42	20.8	0.93

The comparison of denoising methods shows a progressive improvement from conventional statistical methods to deep learning approaches. The Convolutional autoencoder (CAE) produces the best performance, reducing noise standard deviation from ±4.2 to ± 2.5mGal corresponding to 42% noise reduction. This method also achieved the highest signal-to-noise ratio (20.8dB), and structural similarity index (0.91), indicating superior preservation of geological features.

A prominent northeast–southwest-trending gravity gradient identified in the CAE-enhanced anomaly field is interpreted as an intra-basin fault zone. The structure is expressed by an abrupt transition between positive and negative gravity anomalies and separates relatively elevated basement blocks from adjacent sediment-filled depocenters. The fault is most clearly resolved in the CAE output, where gravity gradients increase from approximately 8.3 to 13.7mGal across the interpreted fault boundary.

Estimated Depth to Gravity Anomalies Sources

Depth to anomaly sources was estimated from the residual gravity field derived after unsupervised dimensionality reduction and noise suppression. The interpreted anomalies indicate source depths ranging from 1.2-5km beneath the seafloor. Shallow positive anomalies correspond to thin sediments overlaying basement uplifts, whereas deeper negative anomalies represent sedimentary depocenter and fault-controlled basin (Figure 10). The gravity profile is segmented in five zones of overlapping density contrast, and the interpreted depths delineated for each zone are as well presented. The deepest anomalies 4-5km occur toward the central part of the corridor, suggesting significant crustal thinning and sediment accumulation.

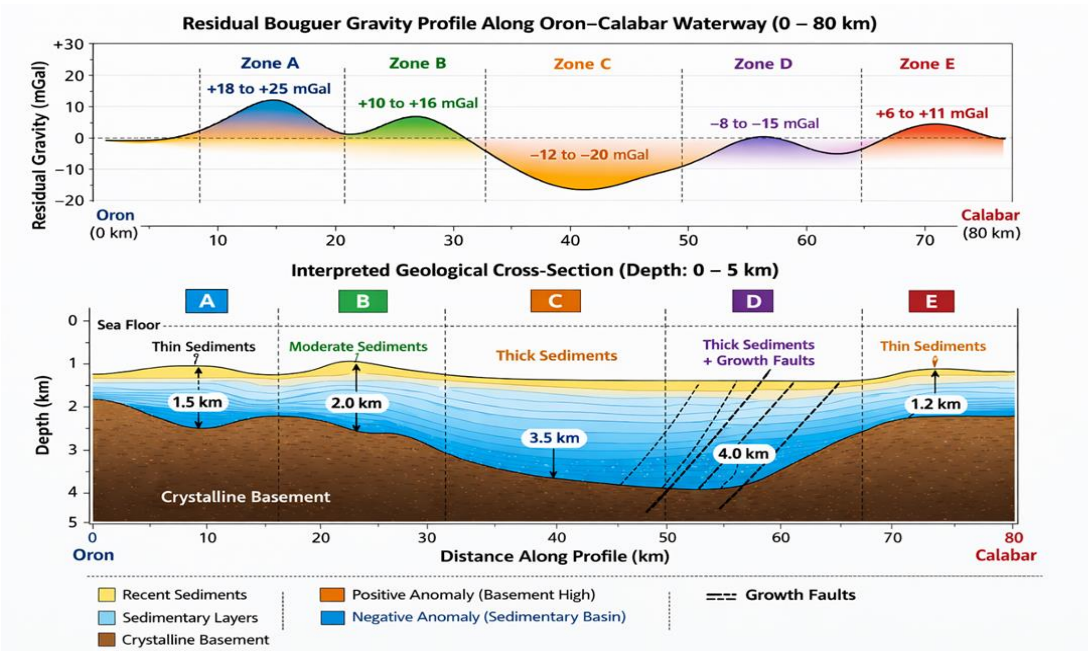

Figure 10: Spatial Profile of Gravity Anomalies and Associated Depths along Oron-Calabar Waterway

Discussion

The gravity driven structural framework of the Oron-Calabar waterway, within the Niger Delta along continental margin of the Gulf of Guinea, offshore Nigeria, is consistent with recent geophysical and tectono-sedimentary investigations of the basin. Modern studies using gravity, aeromagnetic, seismic, and machine-learning approaches confirm that basement configuration, sediment loading, and gravity-driven deformation remain the dominant controls on subsurface architecture across the deltaic margin.

Basement Relief and Structural Control of Basin Geometry

The long wavelength gravity anomalies identified in this study indicate pronounced basement undulation, expressed as alternating structural highs and sediment filled depression. This observation aligns with recent gravity and integrated potential field modelling by Nwankwo et. al. (2021), who demonstrated that basement topography beneath the offshore Niger Delta is highly irregular and exerts first order control on sediment accommodation and basin segmentation. Similarly, structural mapping by Ehirim et. al. (2021), using combined gravity and aeromagnetic inversion, identified basement ridges and troughs that govern local subsidence patterns and depositional architecture. The distribution of regional gravity highs and lows resolved through PCA in the present study reproduces this structural template, confirming that inherited basement morphology continues to influence basin geometry even in heavily sediment loaded offshore zones.

Spatially Variable Sediment Thickness

The extensive negative gravity anomalies interpreted as sediment thickened depocenters, demonstrates rapid clastic influx produces strongly heterogeneous subsidence, loading to localized accommodation zones rather than uniform basin deepening. These findings are consistent with recent quantitative subsidence modelling of the Niger Delta Basin scale loading simulations by Okiwelu et. al. (2010). A 3-D gravity inversion results reported by Lawal et. al. (2023) showed that offshore sediment thickness varies sharply over short distances, particularly where structural confinement enhances compaction and loading. The spatial clustering of gravity minima observed in the present study supports the interpretation of structurally controlled depocenter development.

The gravity-derived structural framework was validated against recent geological and geophysical studies of the Niger Delta Basin. The broad gravity lows identified within the Oron–Calabar waterway are consistent with sediment-filled depocenters and zones of enhanced subsidence reported from gravity and aeromagnetic investigations in the offshore Niger Delta (Ekwok et al., 2021; Bako & Kusche, 2024). Similarly, the gravity highs correspond to basement uplifts and structurally elevated blocks that exert significant control on sediment distribution and basin architecture (Ehirim et al., 2021). The structural gradients and compartmentalized anomaly patterns delineated by PCA, KPCA, and CAE are comparable to the fault-controlled deformation and growth-fault systems widely documented across the Niger Delta margin (Ekwok et al., 2021; Okechukwu et al., 2025). Although direct seismic reflection and borehole data were unavailable for this study, the close agreement between the interpreted gravity anomalies and established regional geological models supports the reliability of the machine-learning-enhanced gravity interpretation and confirms the presence of structurally controlled depocenters, basement highs, and fault-related deformation within the study area.

The nonlinear structural patterns and sharp gravity gradients revealed through KPCA and CAE correspond closely with structural interpretations of gravity driven deformation in Niger Delta. It also supports the work by Ehirim et al. (2021), which shows that growth fault systems remain the primary mechanism for basin compartmentalization in offshore sector of the delta. The compacted anomaly clusters isolated by the convolutional autoencoder (CAE) indicate localized density variations within the sedimentary column and underlying basement. Interestingly, autoencoder-based feature extraction enhances spatial separation of overlapping gravity signals, particularly in sediment rich offshore environment. The high-resolution anomaly segmentation obtained, closely mirror these findings, indicating that localized density contrasts likely reflect structural confinement, variable compaction, and heterogeneous sediment facies distribution. This aligns with the findings on machine-learning assisted gravity interpretation by Ekwok et al. (2021) and Guevara, et. al. (2023). They demonstrated that deep learning decomposition of gravity data can resolve discrete density bodies associated with channelized deposition, structural blocks, and lithologic variability in deltaic basins.

The improved structural clarity observed in the CAE results of this study supports this methodological conclusion and highlights the effectiveness of nonlinear dimensionality reduction techniques for marine gravity interpretation. The results confirm contemporary understanding that basin architecture in complex marine deltaic environments is governed by irregular basement relief controlling subsidence patterns, differential sediment loading producing heterogeneous depocenters, gravity driven growth fault systems segmenting the basin, localized lithologic and compaction related density contrasts.

The spatial distribution of anomalies depths aligns with major structural trends inferred from residual gravity anomalies in the Niger Delta Basin. The observed distribution of interpreted depths aligns with tectonic model of the southern Niger Delta margin, where progressive thickening of sedimentary sequences away from the shoreline and basinward subsidence generate deeper anomalous sources. Within this framework, the clustering of deeper Euler solution (3.5km) toward the offshore end of the survey transect likely corresponds to zones of maximum sediment accumulation and structural depression, controlled by major faults and flexural basin architecture. Collectively, the interpreted anomaly depths from this study not only corroborate findings from other gravity and potential field studies in southern Nigeria (Bako & Kusche, 2024; Osagie et. el., 2021), but also refine the local subsurface structural model for Oron-Calabar waterway.

Although CAE achieved the best denoising performance, the method remains dependent on latent-space dimensionality selection and training parameters. Over-compression may suppress geologically meaningful short-wavelength anomalies, while under-compression may preserve noise. Furthermore, because no ground-truth gravity model exists for the study area, validation relies primarily on internal statistical metrics (SNR and SSIM), and reconstruction error, as well as comparison with established regional geological models.), and comparison with regional geological models. Future studies should integrate seismic reflection and borehole datasets to improve geological validation.

CONCLUSION

This study developed a comprehensive framework for unsupervised dimensionality reduction and noise suppression in marine gravity data acquired along the sedimentary Oron-Calabar coastal corridor, located within the offshore extension of the Niger Delta in the Gulf of Guinea. By utilizing Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Convolutional Autoencoders (CAE), this approach successfully bypassed the limitations of conventional filtering. The application of these techniques demonstrated that while linear methods like PCA effectively isolate dominant basin-scale structural trends, nonlinear frameworks particularly the CAE model provide superior adaptability in noise suppression and

anomaly reconstruction while preserving critical structural edges and gravity field continuity. Consequently, these enhanced gravity products provide a more robust geophysical foundation for geological modelling and sedimentary basin analysis in the region.
While these findings offer critical constraints for local geological mapping, a notable limitation of this framework is its dependence on the quality of initial mobile-platform pre-processing and its computational demand during autoencoder training. Future research should focus on validating these unsupervised models across diverse tectonic settings and integrating them with complementary seismic or magnetic datasets. Refining these models will better support localized coastal development planning and provide data-driven insights applicable to broader offshore resource management and marine geohazard assessments in the Gulf of Guinea.

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