Convolutional Neural Network-Based Separation and Interpolation of Regional and Residual Gravity Anomalies for Application to Subsurface Structure Delineation in the Gongola Basin, Nigeria

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Abstract

The Gongola Basin, a frontier sub-basin of the Benue Trough with recognized hydrocarbon potential, was selected because its gravity data are relatively sparse and noisy, limiting reliable structural interpretation. This study developed a convolutional neural network (CNN)-based framework integrating Fast Fourier Transform (FFT) filtering and U-Net interpolation to separate and reconstruct regional and residual gravity anomalies. FFT filtering effectively isolated long-wavelength regional fields from short-wavelength residual anomalies, while the CNN reconstructed residual anomaly maps with improved spatial continuity and preservation of structural boundaries. The resulting maps delineated sedimentary depocentres, basement highs, and fault-controlled structures associated with prospective hydrocarbon systems. Uncertainty analysis indicated stable predictions with minimal systematic bias. The proposed framework outperformed conventional interpolation approaches by preserving subtle geological features and reducing smoothing effects. These results demonstrate that integrating FFT filtering with deep learning provides an effective and scalable approach for gravity interpretation and petroleum exploration in data-limited frontier sedimentary basins.

Keywords: Gravity anomalies, Convolutional Neural Network, FFT filtering, petroleum exploration, regional and residual gravity, Gongola Basin.

Introduction

Gravity anomaly analysis remains one of the most important geophysical techniques in petroleum exploration for investigating subsurface density variations and delineating geological structures favorable for hydrocarbon accumulation (Hinze *et al*., 2013; Wang, Li, & Zhao, 2022). Although gravity methods do not directly detect hydrocarbons, they provide essential information on basin architecture, sediment thickness, basement morphology, fault systems, and structural traps that guide seismic exploration and drilling operations (Sun & Chen, 2023). In sedimentary basins, observed gravity fields are generally composed of superimposed regional and residual anomaly components. The regional anomaly is commonly associated with deep crustal and lithospheric structures, whereas the residual anomaly reflects shallower geological features such as faults, folds, intrusions, and sedimentary depocentres that are directly related to hydrocarbon prospectivity (Abdul Fattah *et al*., 2019; Mula & Muhammed, 2024).

Accurate separation of regional and residual gravity anomalies is therefore essential for reliable geological interpretation and petroleum system evaluation. Conventional techniques such as polynomial trend analysis, upward continuation, Fourier filtering, moving-average filtering, and wavelet decomposition have been widely applied in gravity anomaly separation (Doğru *et al*., 2021; Sehah *et al*., 2022). However, these approaches are often affected by operator subjectivity, parameter dependency, spectral overlap, and reduced performance in sparse or noisy datasets (Kletetschka, 2024). Traditional interpolation techniques also tend to oversmooth gravity fields, thereby suppressing subtle geological signatures that are critical for hydrocarbon exploration (Li *et al*., 2024).

Recent advances in artificial intelligence and deep learning have introduced Convolutional Neural Networks (CNNs) as highly effective tools for geophysical data analysis and interpretation (Huang *et al*., 2021; Bai *et al*., 2024). CNNs possess the capability to learn nonlinear spatial relationships and extract multiscale features from image-like datasets such as gravity anomaly maps (Li, 2023). Their ability to preserve structural boundaries, reconstruct missing data, and reduce interpolation artefacts makes them particularly suitable for gravity anomaly enhancement and subsurface structural interpretation (Gu *et al*., 2023). Several recent studies have successfully applied CNNs to gravity inversion, interpolation, and geophysical imaging, demonstrating superior performance compared with many classical methods (Bai *et al*., 2024; Huang *et al*., 2021).

The Gongola Basin, located within the Upper Benue Trough, is one of Nigeria's inland sedimentary basins that have attracted increasing interest for hydrocarbon exploration due to its favorable tectono-sedimentary evolution (Obaje, 2009; Nwajide, 2013). Previous gravity-based investigations within the basin identified major depocentres, basement highs, and tectonic structures associated with petroleum prospectivity (Avbovbo *et al*., 1986). More recent geological, geophysical, and petroleum system studies have corroborated these interpretations, demonstrating that basement architecture and structurally controlled depocentres strongly influence hydrocarbon generation, migration pathways, and reservoir distribution in the Gongola Basin and Kolmani area (Epuh & Joshua, 2017; Didi *et al*., 2024; Hamis *et al*., 2024). Despite these advances, the application of deep learning techniques for gravity anomaly separation and interpolation in the basin remains limited. Consequently, this study develops a CNN-based framework for the separation and interpolation of regional and residual gravity anomalies in the Gongola Basin using satellite-derived and published gravity datasets. The study seeks to improve gravity anomaly interpretation and enhance the delineation of exploration-relevant geological structures.

Statement of the Problem

Interpretation of gravity anomaly data in sedimentary basins is often complicated by the superposition of regional and residual gravity signals (Sun & Chen, 2023). Conventional separation methods such as polynomial fitting, upward continuation, and spectral filtering frequently encounter difficulties in distinguishing overlapping wavelength components, particularly in structurally complex basins such as the Gongola Basin (Doğru *et al*., 2021). These methods also rely heavily on subjective parameter selection, which may introduce inconsistencies and distort important geological features (Kletetschka, 2024).

In addition, gravity datasets in frontier sedimentary basins are commonly sparse, irregularly distributed, or contaminated by noise, thereby limiting the effectiveness of conventional interpolation methods such as kriging and inverse distance weighting (Li *et al*., 2024). These approaches often oversmooth anomaly fields and suppress subtle structural signatures that are essential for petroleum exploration and reservoir characterization (Mula & Muhammed, 2024).

Although recent advances in deep learning, particularly convolutional neural networks, have demonstrated promising results in geophysical inversion, interpolation, and structural interpretation (Huang *et al*., 2021; Bai *et al*., 2024), their application to regional–residual gravity anomaly separation and interpolation within the Gongola Basin remains largely unexplored. There is therefore a need for a robust, automated, and data-driven framework capable of accurately separating gravity components, preserving exploration-scale geological structures, and improving interpolation performance in sparse gravity datasets.

Aim and Objectives of the Study

The main objective of this study is to develop a CNN-based framework for the separation and interpolation of regional and residual gravity anomalies in the Gongola Basin, Nigeria.

The specific objectives of the study are to:

1. Acquire, preprocess, and separate the Bouguer gravity anomaly data of the Gongola Basin into regional and residual components using FFT-based filtering techniques.
2. Develop and apply a CNN-based interpolation model for reconstructing residual gravity anomaly fields and evaluate its effectiveness in preserving geological structures for petroleum exploration.

Research Questions

The study seeks to answer the following research questions:

1. How effective is FFT-based filtering in separating the Bouguer gravity anomaly field into regional and residual components within the Gongola Basin?
2. How effective is the CNN-based interpolation model in reconstructing residual gravity anomaly fields and enhancing geological interpretation for petroleum exploration?

Literature Review

Several studies have demonstrated the importance of gravity-based techniques and advanced computational approaches in subsurface geological interpretation and petroleum exploration. Spectral and gravity tensor analyses have proven effective for identifying structural trends, sediment thickness, and petroleum-related anomalies within sedimentary basins (Sehah *et al*., 2022; Doğru *et al*., 2021). Satellite-derived gravity datasets processed using platforms such as Oasis montaj have also been successfully applied for Bouguer anomaly mapping, structural interpretation, filtering, and contouring, although these methods remain computationally intensive and often require advanced reduction procedures (Darisma *et al*., 2019; Ayuba & Nur, 2018; Alamri & Ali, 2021).

Recent advances in deep learning have significantly improved geophysical data interpretation and interpolation. CNN-based models have demonstrated strong capabilities in capturing nonlinear geophysical relationships, integrating heterogeneous gravity datasets, and improving structural interpretation for petroleum exploration (Gu *et al*.; Li *et al*., 2024; Li, 2023). Similarly, satellite gravity data have been widely applied in lithospheric, geothermal, and tectonic studies related to petroleum systems, with studies confirming the value of gravity-based modeling for identifying petroleum maturity zones and subsurface structural features (Abdul Fattah *et al*., 2019; Arisalwadi et al., 2023).

Gravity inversion and spectral analysis techniques have also been widely used for basement depth estimation, fault delineation, and subsurface structural interpretation (Cai & Zhdanov, 2015; Mula & Muhammed, 2024; Yusvinda *et al*., 2021). Automated approaches involving horizontal gradients, upward continuation, gravity gradient tensors, and Euler deconvolution have shown effectiveness in fault and lineament mapping; however, they often require extensive manual processing and parameter selection (Kamto *et al*., 2021; Kletetschka, 2024). Machine learning and deep learning methods are therefore increasingly being explored to improve computational efficiency, automation, and interpretation reliability in gravity-based exploration (Camacho & Alvarez, 2021; Wang *et al*., 2022; Sun & Chen, 2023).

Furthermore, deep learning applications in inversion and interpolation have expanded across geophysical disciplines. Neural network approaches have demonstrated superior prediction accuracy and computational efficiency compared with traditional interpolation methods (Chahrour & Wells, 2022). CNN-based inversion frameworks have successfully generated subsurface models with distinct geological boundaries and reduced non-uniqueness problems associated with conventional inversion techniques (Huang *et al*., 2021; Bai *et al*., 2024). Related studies in noise detection, digital elevation model (DEM) enhancement, hydrological anomaly modeling, and satellite gravity integration further confirm the adaptability of deep learning for geophysical data reconstruction and anomaly interpretation (Morales *et al*., 2021; Kandil *et al*., 2024; Gou & Soja, 2024; Abulaitijiang *et al*., 2021; Gilardoni *et al*., 2013). Collectively, these studies highlight the growing significance of integrating gravity analysis with deep learning techniques to improve petroleum exploration and subsurface geological interpretation.

Methodology

Data Acquisition and Preparation

The study utilized three categories of gravity datasets:

1. Satellite-derived gravity models from the GOCO06s Model.
2. Published ground gravity datasets for the Gongola Basin obtained from previous studies.
3. Synthetic gravity anomaly fields generated from forward models of prisms, sills, and dipping blocks for CNN training and validation.

The gravity datasets were converted into standardized gridded formats suitable for spectral analysis and deep learning applications. Gravity anomaly values were normalized to improve model stability and facilitate comparative interpretation.

FFT-Based Regional-Residual Separation

The Bouguer gravity anomaly field was separated into regional and residual components using two-dimensional Fast Fourier Transform (FFT) filtering techniques using equation 1;

$$\mathrm{H}\left(k_{x,}k_y\right) = \int_{-oo}^{+oo}\int_{-oo}^{+oo} h(x,y)\,.\,e^{-i(k_x x+k_y y)}dx.\mathrm{dy} = \mathrm{F}\left[h\left((x,y)\right)\right], \quad [1]$$

The FFT approach decomposed the gravity field into frequency components, enabling the extraction of long-wavelength regional anomalies and short-wavelength residual anomalies.

The filtering workflow involved loading gridded gravity anomaly data into a Python processing environment, followed by the application of tapering and zero-padding techniques to minimize spectral leakage and edge effects using equation 2;

$$\mathrm{h}\ (\mathrm{x},\mathrm{y}) = \frac{1}{4\pi^2}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} H\left(k_{x,}k_y\right).\,e^{i(k_x x+k_y y)}dk_x dk_y = F^{-1}\left[H\left(k_x,k_y\right)\right] \quad [2]$$

Subsequently, the two-dimensional FFT spectrum of the gravity field was computed to transform the data into the frequency domain using equation 3 as follows;

$$\mathrm{H}(u,v) = \int_{-oo}^{+oo}\int_{-oo}^{+oo} h(x,y)\,.\,e^{-2\pi i(ux+vy)}dx.\mathrm{dy} = \mathrm{F}\left[h\left((x,y)\right)\right], \quad [3]$$

Gaussian low-pass filters were then constructed using selected cutoff wavelengths to isolate long-wavelength regional components from short-wavelength residual signals using equation 4 as thus;

$$\mathrm{h}\ (\mathrm{x},\mathrm{y}) = \frac{1}{4\pi^2}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} H(u,v)\,.\,e^{2\pi i(ux+vy)}dudv = F^{-1}[H(u,v)], \quad [9]$$

Finally, inverse FFT operations were applied to reconstruct the regional and residual gravity anomaly maps in the spatial domain.

Several cutoff wavelengths ranging between 50 km and 100 km were tested to determine the optimal separation scale for the Gongola Basin. Residual anomaly maps were subsequently used for geological interpretation and CNN-based interpolation.

Python libraries including NumPy, SciPy, Matplotlib, Xarray, and NetCDF4 were employed during the analysis (Figure 1). The procedure was carried out as follows;

i. The regional-residual filtering was done to isolate local anomalies from broader trends The Bouguer anomaly was decomposed into regional and residual components using Fast Fourier Transformation filtering in which Gradient analysis for fault mapping.

ii. Structural highs and lows indicative of petroleum traps.

iii. The tools used are: NumPy, SciPy, and Matplotlib libraries in Python.

Therefore, the geophysical feature derivation, where gridded gravity anomaly data are processed and features such as FVD, THD, TA and AS were extracted. Here is the algorism;

Create working directory; mkdir ~/goco_06s/gravity

Activate Miniconda environment; conda activate goco_env

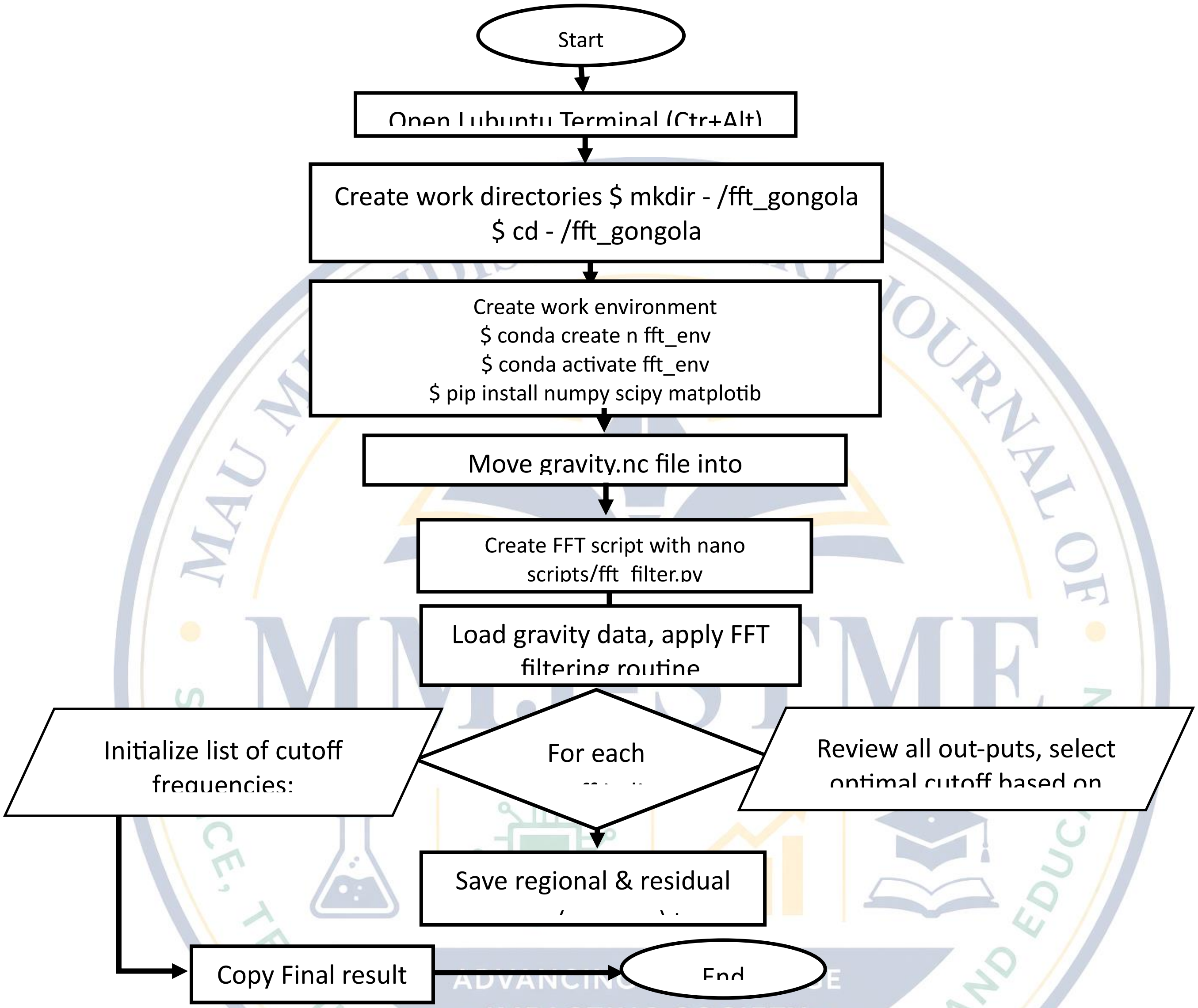

Figure 1: FFT Regional-Residual Separation (Source: Author`s work)

Navigate to working directory; cd ~/goco_06s/gravity

Convert GOCO06s.gfc to NetCDF using Python (written in nano); nano convert_gfc_to_nc.py

Inside the script, use custom or existing tools to parse GOCO06s.gfc to NetCDF

Ctrl + 0 the enter to save

Ctrl + X exit

Run the script; python3 convert_gfc_to_nc.py

Plot or extract statistics; nano plot_features.py

Use matplotlib, numpy, etc.; python3 plot_features.py.

CNN-Based Interpolation of Residual Gravity Anomalies

Residual gravity anomaly maps were transformed into image-like arrays suitable for deep learning analysis. Missing and noisy regions were artificially introduced into the datasets to simulate sparse observations and generate training samples.

A U-Net-based Convolutional Neural Network architecture was developed using TensorFlow/Keras for residual gravity interpolation. The CNN architecture consisted of convolutional layers, pooling layers, and upsampling layers designed to capture both local and global spatial relationships within the gravity field.

The model training procedure involved preparing image patches from the residual gravity anomaly grids and subsequently dividing the datasets into training, validation, and testing subsets. The CNN model was then trained using supervised learning techniques, while optimization was achieved through the use of Mean Squared Error (MSE) and Structural Similarity Index (SSIM) loss functions. Model performance was evaluated using Root Mean Square Error (RMSE), visual inspection of reconstructed anomaly fields, and cross-validation procedures to assess prediction accuracy and generalization capability.

The trained CNN model was subsequently used to reconstruct continuous residual gravity anomaly surfaces across the Gongola Basin. Model performance was assessed using cross-validation, visual comparison of the reconstructed and reference anomaly maps, and the root mean square error (RMSE) as a measure of prediction accuracy (Hastie *et al*., 2009). Here is algorithm;

```
# Prepare image dataset from residual grids; nano prepare_images.py
python3 prepare_images.py
# Write and train CNN interpolation model
nano cnn_interpolation.py
python3 cnn_interpolation.py
# Output: cnn_interpolated_residual.png.
```

Results

Result of Regional and Residual Gravity Anomaly Separation

The FFT filtering successfully separated the gravity field into regional and residual components (figure 2). The regional gravity anomaly map exhibited broad long-wavelength features characterized by a pronounced north-south gravity gradient across the study area. Higher gravity values were observed in the southern part of the basin, gradually transitioning into lower gravity values toward the northern region.

The residual gravity anomaly map highlighted localized short-wavelength anomalies associated with shallow geological structures. Negative residual anomalies were concentrated within the basin interior, while positive anomalies were distributed around basement highs and structurally elevated regions. The regional anomalies reflected deep crustal and lithospheric structures, whereas the residual anomalies emphasized exploration-scale geological features such as fault-controlled depressions, basement uplifts, and sedimentary depocentres.

4.2 CNN-Based Interpolation Results

The CNN interpolation model successfully reconstructed the residual gravity anomaly field with improved spatial continuity and reduced interpolation artefacts (Figure 3). The interpolated residual map displayed smooth yet structurally consistent anomaly transitions across the basin.

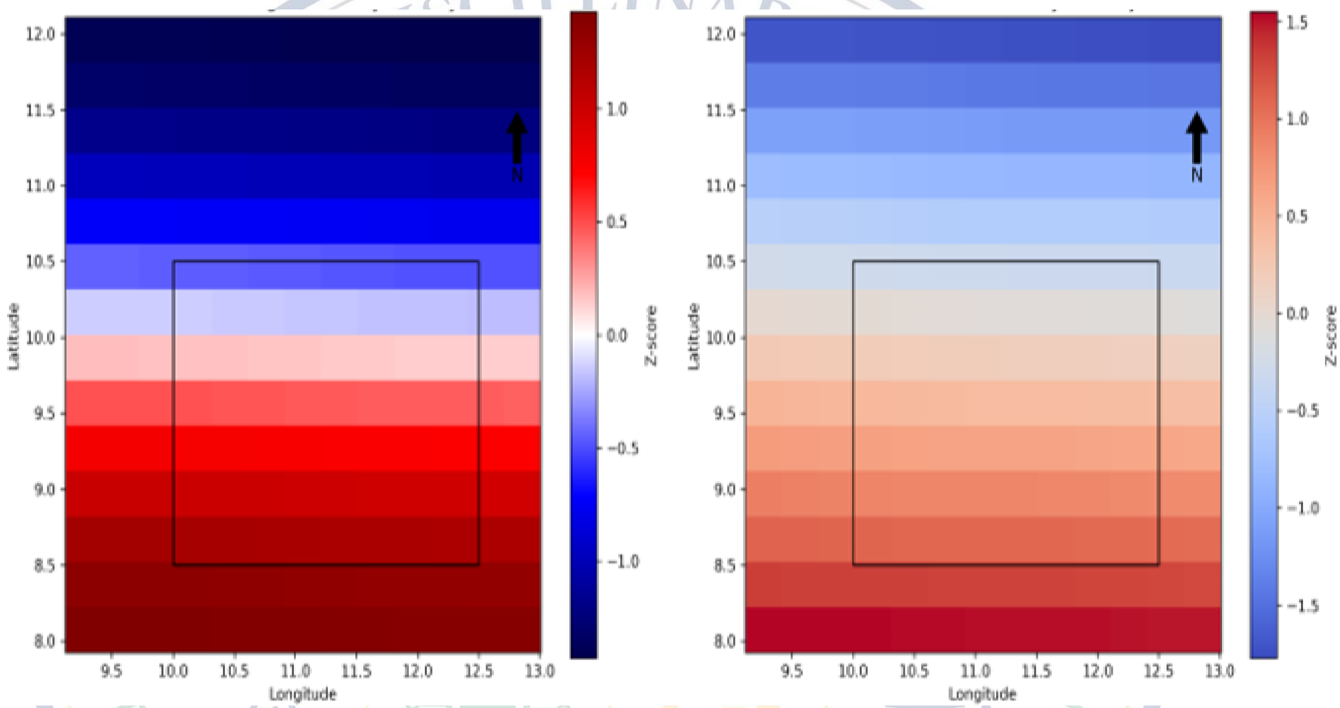

Figure 2: Regional and Residual Gravity Anomalies Maps (Source: Author`s work)

Positive residual anomalies dominated the northern section of the study area, indicating denser crustal materials, while negative anomalies were concentrated within the central and southern basin regions, suggesting thicker sedimentary accumulations.

Compared with traditional interpolation methods, the CNN approach preserved anomaly edges and subtle structural variations more effectively while minimizing over-smoothing effects.

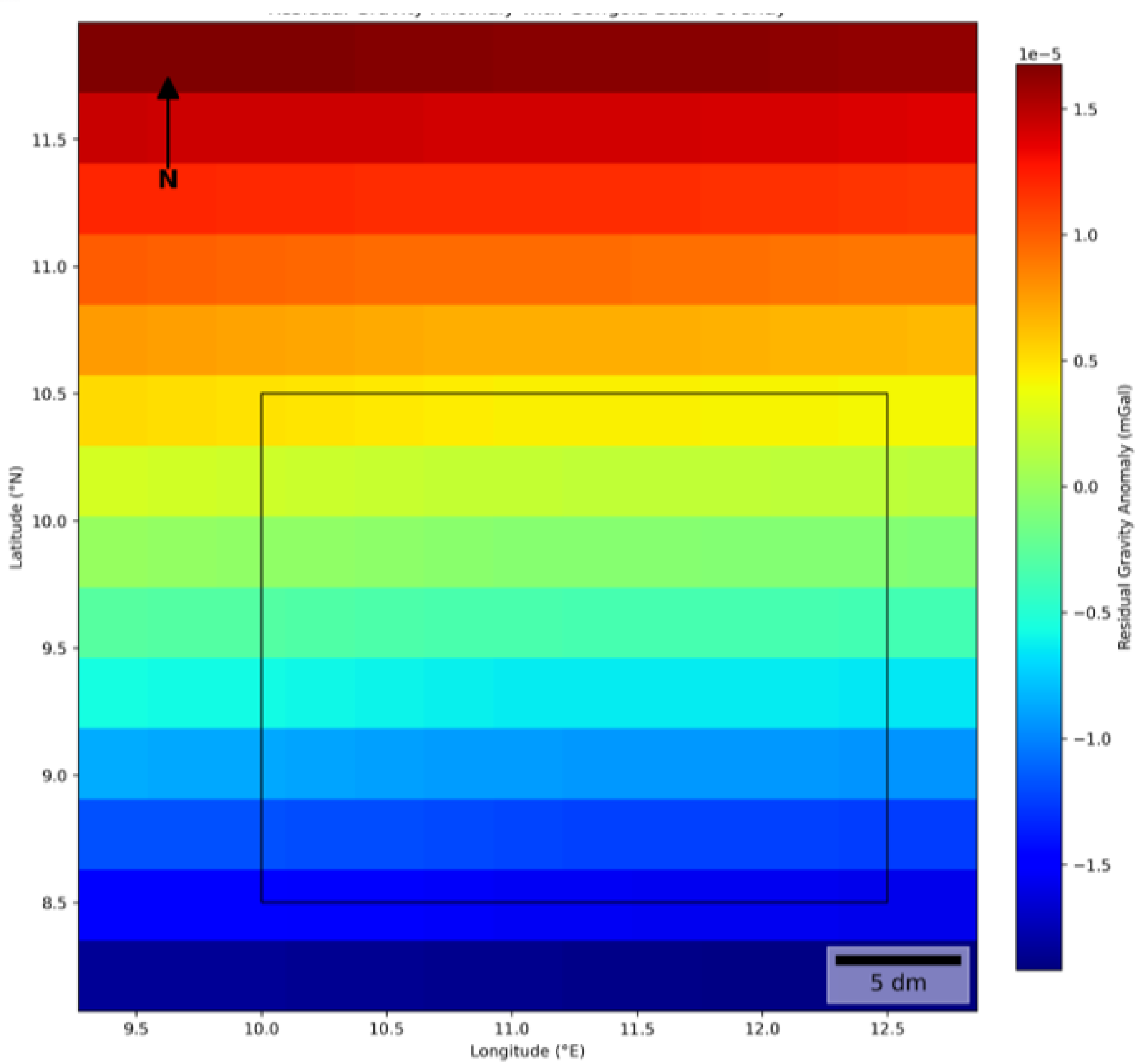

Figure 3: Interpolated Residual Gravity Anomalies Map (Source: Author`s work)

4.3 Uncertainty Analysis

Uncertainty mapping revealed that the CNN interpolation did not introduce systematic upward or downward bias into the residual gravity predictions (Figure 4). Higher uncertainty values were mainly concentrated around structurally complex regions and basin margins where training data coverage was relatively sparse.

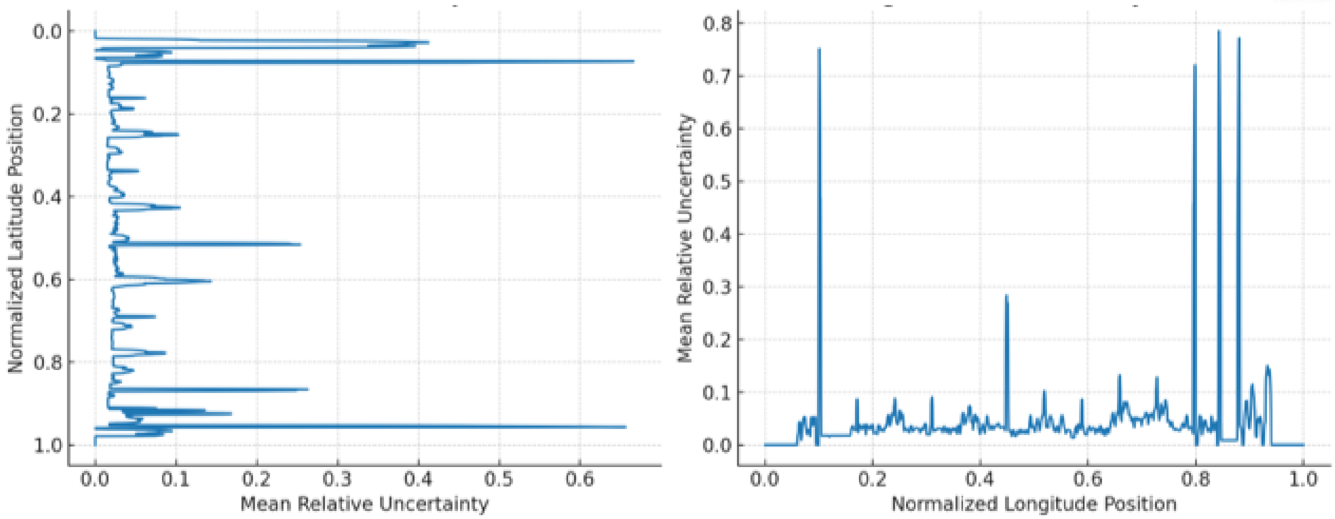

Figure 4: *Sensivity Test of Resual Anomalies Interpolation* (Source: Author`s work)

The uncertainty distribution was largely random and spatially balanced, indicating stable model performance suitable for petroleum exploration applications.

Discussion of the Findings

The successful separation of regional and residual gravity anomalies demonstrates the effectiveness of FFT filtering in distinguishing deep-seated crustal structures from shallow exploration-scale geological features. The regional gravity gradient observed across the Gongola Basin likely reflects tectonic tilting, crustal thinning, and lithospheric variations associated with the extensional evolution of the Upper Benue Trough.

The residual anomaly field provided clearer delineation of localized geological structures such as sedimentary depo-centers, basement highs, and fault systems. Negative residual anomalies within the basin interior are interpreted as low-density sedimentary accumulations that may represent favorable hydrocarbon generation zones due to increased burial depth and thermal maturation. Positive residual anomalies may correspond to basement intrusions or uplifted crystalline structures capable of influencing hydrocarbon migration pathways and trap formation.

The CNN-based interpolation approach demonstrated significant advantages over conventional interpolation techniques. Unlike kriging and inverse distance weighting methods that often oversmooth gravity data, the CNN model effectively preserved subtle structural patterns and anomaly boundaries. This improved structural fidelity is particularly important for petroleum exploration because subtle gravity variations may correspond to stratigraphic traps, fault-controlled reservoirs, or lithological boundaries.

The study further confirms the growing relevance of deep learning approaches in geophysical interpretation. By learning nonlinear spatial relationships within gravity datasets, CNNs provide a robust framework for handling sparse and noisy geophysical data. The integration of residual gravity anomalies into CNN workflows therefore enhances exploration-target detection and improves the reliability of basin-scale geological interpretation.

Nevertheless, the effectiveness of CNN-based methods remains dependent on the quality and representativeness of training datasets. Although synthetic models provided useful training examples, future studies should incorporate additional geological constraints, seismic datasets, and well-log information to further improve model generalization and physical consistency.

Conclusion

This study developed a Convolutional Neural Network-based workflow for the separation and interpolation of regional and residual gravity anomalies in the Gongola Basin, Nigeria. FFT filtering successfully decomposed the Bouguer gravity field into regional and residual components, thereby enhancing the interpretation of both deep crustal structures and shallow exploration-scale geological features.

The CNN interpolation model effectively reconstructed residual gravity anomaly fields while preserving structural continuity and reducing interpolation artefacts. The resulting residual anomaly maps revealed significant geological features including sedimentary depocentres, basement highs, and structural boundaries associated with petroleum prospectivity within the Gongola Basin.

Overall, the integration of FFT filtering and CNN-based interpolation provides a reliable and scalable framework for gravity anomaly interpretation in frontier sedimentary basins. The methodology offers substantial potential for improving petroleum system analysis and supporting hydrocarbon exploration in underexplored regions.

Recommendations

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

1. Future studies should integrate seismic reflection data, well logs, and geological mapping with CNN-derived gravity anomaly interpretations to improve model validation and geological reliability.
2. Physics-informed deep learning models should be explored to constrain CNN predictions using geophysical principles and reduce the possibility of nonphysical anomaly reconstruction.
3. Additional uncertainty quantification techniques such as Bayesian CNNs and ensemble learning approaches should be incorporated into future gravity interpretation workflows.
4. Higher-resolution airborne and terrestrial gravity datasets should be combined with satellite gravity models to improve structural delineation within the Gongola Basin.

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