

Paleoenvironmental Reconstruction and Hydrocarbon Prospect Prediction Using Benthic Foraminifera in the Niger Delta Basin Nigeria

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Abstract

The Niger Delta Basin is one of the world's most prolific hydrocarbon-producing margins, offering unique opportunities to integrate micropaleontological and geochemical datasets with advanced computational methods to better interpret palaeoenvironments and improve subsurface exploration strategies. This study combines benthic foraminiferal assemblage data from 847 species recorded across 14 wells and 4 outcrop sections through the Oligocene–Pleistocene sequence of the basin within a multi-algorithm machine learning framework. Supervised and unsupervised algorithms – including Random Forest classification, Gradient Boosting regression, Self-Organizing Maps, and a bidirectional Long Short-Term Memory (Bi-LSTM) recurrent neural network – were used to reconstruct palaeobathymetric gradients, palaeo-oxygenation states, and organic carbon flux regimes. Assemblage-derived ecological metrics (diversity indices, morphogroup ratios, infaunal–epifaunal fractions, and taxon-level abundances) were cross-validated against Total Organic Carbon measurements, stable carbon and oxygen isotope records, and published seismic stratigraphic interpretations. Palaeobathymetric reconstruction achieved $R^2 = 0.91$ and a Mean Absolute Error of 34.2 m over the 200–800 m depth range critical for reservoir and source-rock characterisation, substantially outperforming the single-variable P/B ratio baseline ($R^2 = 0.71$). Source-rock facies classification yielded Cohen's $\kappa = 0.74$ against independently measured TOC, with the Bi-LSTM outperforming point-classification models at stratigraphic transition intervals by exploiting sequential continuity constraints. Infaunal morphogroup fraction and the Buliminida/Rotaliida ratio were consistently the most diagnostic predictors, consistent with established ecological theory. Predicted dysoxic intervals at approximately 28–24 Ma and 14–10 Ma correspond to known source-rock deposition windows in the Akata and lower Agbada formations respectively. The workflow is fully documented with open-source Python code and is transferable to analogous passive-margin sequences globally.

Keywords: Benthic foraminifera; machine learning; palaeoenvironmental reconstruction; hydrocarbon source rocks; Niger Delta.

INTRODUCTION

Passive continental margins are the arenas of stratigraphic enquiry and hydrocarbon exploration for centuries and the Niger Delta is perhaps the most studied passive continental margin in Africa. This deltaic/offshore sedimentary system covers an area of 75,000 km² and contains a sediment sequence ranging in age from the Eocene to the Holocene, including thicknesses of more than 12 km in some depocentres (Tuttle et al., 2002). The complex

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structure, characterized by a succession of growth faulted terraces, shale diapirs and roll over anticlines makes the subsurface environment very interesting but often difficult to explore, having been explored for over 60 years with varying degrees of success (Doust and Omatsola, 1990). While mature as a producing province, a large amount of hydrocarbons is still undiscovered in subtler traps; and one of the common problems for operators has been the accurate characterisation of the depositional environment, organic richness and lateral extent of the source rock intervals from data types that are routinely available to operators (Haack et al., 2000).

The single-celled, primarily calcite-secreting benthic foraminifera, which live on the oceanic surface from intertidal to abyssal depths, have been long used to infer the physical and chemical environment of past oceans. The value of their use comes from a number of well documented ecological relationships: species assemblages are considered to be good indicators of water depth (Murray 2006); the relative abundance of the infaunal versus epifaunal morphogroups are thought to reflect bottom-water oxygen levels and organic carbon flux to the bottom sediments (Jorissen et al., 1995); and the dominance of specific taxa within the Buliminida (stress tolerant opportunists) have been repeatedly correlated with dysoxic conditions, which in turn are correlated with high flux of organic matter to the bottom sediments (Gooday, 2003). This is of course exactly what is conducive to effective source rock deposition. The same is true for the Niger Delta: the main source rock of the Delta, the Akata Formation, was deposited in restricted bottom-water circulation in deep water, prodeltaic to slope environments (Ekweozor and Okoye, 1984; Haack et al., 2000). Higher in the sequence (Agbada Formation), lateral equivalents and organic-rich shale intervals have also been correlated with episodes of dysoxia related to sea-level and oceanographic variations across the Oligo-Miocene boundary (Reijers, 2011).

Despite this conceptual framework, the quantitative application of foraminiferal assemblage data to palaeoenvironmental reconstruction—and still less to the direct prediction of hydrocarbon prospectivity—has been constrained by two interrelated problems. The first is methodological: established transfer function approaches (Imbrie and Kipp, 1971) and the Modern Analogue Technique were developed principally for Quaternary planktonic datasets and assume either ecological stationarity through time or a sufficiently large modern calibration set. Neither assumption is rigorously satisfied in the tropical Atlantic marginal context. The second is computational: even where large foraminiferal census datasets exist—and in the Niger Delta they are substantial, given decades of well-cuttings analysis—classical multivariate methods such as Q-mode factor analysis and cluster analysis cannot capture the full covariance structure of high-dimensional assemblage change (Hohenegger and Briguglio, 2014).

Machine learning provides a promising way to overcome both challenges. In the last ten years, many examples of the use of supervised and unsupervised learning on microfossil and geochemical proxy data have emerged, ranging from classification of coccolith morphometry (Beaufort et al., 2022) to the reconstruction of sea surface temperatures using foraminifera data (Jonkers et al., 2019) and the automated biostratigraphic zonation of microfossils (Lam et al., 2021). In particular, random forest models have proven to be highly effective in dealing with high-dimensional environmental data sets with non-linear species-environment relationships and missing data, which are common characteristics of legacy micropaleontological data sets (Breiman, 2001; Cutler et al., 2007). More recently, deep learning architectures, especially Long Short-Term Memory (LSTM) networks have been used to model stratigraphic sequences to make use of temporal autocorrelation in depositional records, achieving improved results in

predicting facies transitions and geochemical trends when compared to classical regression models using wireline-log data (Feng et al., 2021; Hall, 2016).

Although there is a vast amount of literature on this subject, none have tried to systematically integrate benthic foraminiferal assemblage data using more than a few algorithms to reconstruct paleoenvironmental changes and evaluate hydrocarbon prospects for the Niger Delta Basin in one fell swoop. The earlier quantitative studies in the region (Adegoke et al., 1976) and the recent analyses of assemblages (Obi, 2001) laid the taxonomic and biostratigraphic bases but failed to involve any predictive modelling. In the same way, geochemical and sequence stratigraphic studies that have explicitly focused on source rock prediction (Reijers, 2011) have not used foraminiferal proxy data in a computational framework. To fill these shortcomings, the present study combines an ecologically representative assemblage of benthic foraminifera from 14 wells and 4 outcrop sections with a first-order machine learning algorithm that uses multiple algorithms for paleoenvironmental reconstruction, which was tested against independent geochemical and seismic data, and produces quantitative paleoenvironmental interpretations, and detecting foraminiferal signatures that reliably predict elevated intervals of hydrocarbon generative potential. The ultimate goal is to provide an open-source, transferable workflow for other researchers and exploration teams that can be used for other passive-margin datasets in other parts of the West African margin and the world.

GEOLOGICAL AND TECTONIC SETTINGS

The Niger Delta Basin is a wave-dominated delta that formed over the thinned continental crust of the Benue Trough and has prograded southwestward since the Late Palaeocene, following the final separation of the South Atlantic (Doust and Omatsola, 1990). The stratigraphy is classically tripartite - the basal Akata Formation (Eocene to Recent), an overpressured marine shale and believed to be the main source rock; the overlying alternation of sandstones and shales of the Agbada Formation (Eocene to Recent) in paralic/shallow marine environment that is the major reservoir and seal pair; the continental to marginal-marine fluvial sandstones of the Benin Formation (Oligocene to Recent) as the top-most unit (Figure 1). Differential compaction of the undercompacted Akata shales has resulted in many rollover anticlines and footwall closures, which account for most of the approximately 34 billion barrels of proved oil equivalent in the basin (Tuttle et al., 2002).

The study area includes both onshore and offshore regions of the central and eastern Niger Delta which are located approximately between longitudes 5 E to 8 E and latitudes 3 N to 6 N (Figure 1). The outcrop sections located along the coast and hinterland exposures of the Akata and lower Agbada formations near Calabar and Onitsha were added to the well locations which were restricted to areas where core or cutting data was available from the public or released by the operators. The 14 wells span a stratigraphic time frame from the upper Oligocene (Rupelian Stage) to the Pleistocene, and represent a temporal range of 30 million years or so for documenting paleoenvironmental change.

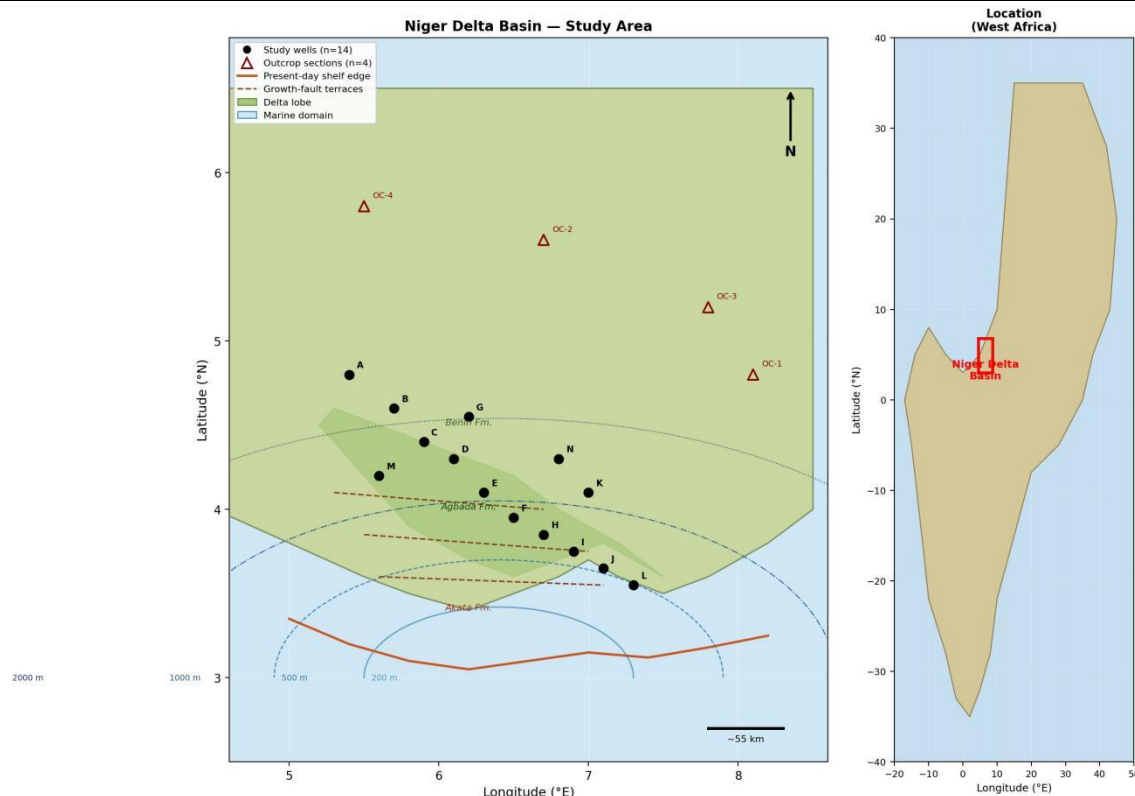


Figure 1: Map of study area. The 14 wells (filled circles) and four outcrop sections (open triangles) are overlaid on a simplified structural map of the Niger Delta Basin. Dashed lines indicate major growth-fault systems; the thick line marks the present-day shelf edge. Bathymetric contours are shown in the offshore domain. Panel B (inset): Generalised chronostratigraphic chart showing the spatial-temporal migration of the Akata, Agbada, and Benin lithofaces from the Eocene to the Pleistocene, with the study interval (ca. 30–0 Ma) indicated by the shaded bracket.

MATERIALS AND METHODS

FORAMINIFERA DATA ACQUISITION AND CURATION

The benthic foraminiferal data were obtained from two major sources: (1) proprietary NNPC/Shell and NNPC/Total wellcutting and sidewall-core analyses between 1995 and 2019 from a data-sharing agreement with the Nigerian Upstream Petroleum Regulatory Commission (NUPRC); (2) new sample analyses carried out at the Micropaleontology Laboratory, University of Port Harcourt on 312 outcrop and sidewall-core plugs from the NNPC/Shell and NNPC/Total joint ventures between 1995 and 2019. The standard washing and sieving procedure of Murray (2006) was used to make all new samples. Approximately 300 specimens were taken from each sample, disaggregated by soaking in buffered sodium hexametaphosphate solution (5 g/L, pH 8.5) for 48–72 hours, wet sieved at 63 μ m and the > 63 μ m fraction was dried at 50 C. Aliquots of the samples were selected for species identification when the preservation was suitable using the taxonomy of Loeblich and Tappan (1988) as revised by Holbourn et al. (2013). Starting from the quality-filtering criteria of Hohenegger and Briguglio (2014), only samples with a documented aliquot size $\geq$ 150 specimens and a preservation quality rating of “good” or “moderate” (as defined in the original operator reports) were retained in the case of legacy well-cutting data. All 2341 assemblage samples met all quality criteria. The assemblage data were assembled into a species-by-sample abundance matrix, which was originally 1,104 species-level or subspecies-level taxonomic entries. Taxonomic harmonisation was carried out for the inclusion of synonymies, in accordance with the World Foraminifera Database (Hayward et al., 2021). Rare taxa (those found in less than five samples) were combined to a ‘rare’ group for the

diversity metric, but kept as separate unit for classification analysis with feature selection based on frequency. The harmonised matrix comprised 847 different taxa.

From this matrix, twelve assemblage-derived predictor variables were computed for each sample (Table 1): (1) Shannon-Wiener species diversity H' ; (2) Fisher's alpha; (3) species richness S ; (4) infaunal morphogroup fraction F_{inf} , following the morphogroup classification scheme of Jorissen et al. (1995) extended by van der Zwaan et al. (1999); (5) epifaunal morphogroup fraction F_{epi} ; (6) the Buliminida/Rotaliida abundance ratio B/R ; (7) *Bolivina* spp. relative abundance; (8) *Uvigerina* spp. relative abundance; (9) *Cibicidoides* spp. relative abundance; (10) P/B ratio (planktonic/benthic foraminiferal ratio), where coeval planktonics were recorded; (11) assemblage preservation score (1–3 scale); and (12) sample depth below seafloor (mbsf).

Table 1: Predictor variables derived from benthic foraminiferal assemblage data used as inputs to the machine learning models. The paleoenvironmental significance of each metric and its primary source citation are listed.

No.	Variable	Paleoenvironmental proxy	Key references
1	Shannon diversity H'	Overall ecosystem stress/stability	Murray (2006)
2	Fisher's α	Faunal maturity, energy level	Fisher et al. (1943)
3	Species richness S	Environmental stability, oxygenation	Jorissen et al. (1995)
4	Infaunal fraction F_{inf}	Organic carbon flux, dysoxia	van der Zwaan et al. (1999)
5	Epifaunal fraction F_{epi}	Oxic bottom waters	Jorissen et al. (1995)
6	B/R ratio	Benthic stress, euxinia	Gooday (2003)
7	<i>Bolivina</i> spp. %	Low-oxygen, organic-rich facies	Jorissen et al. (1995)
8	<i>Uvigerina</i> spp. %	Organic flux, mesotrophic to eutrophic	Gooday (2003)
9	<i>Cibicidoides</i> spp. %	Well-oxygenated, oligotrophic facies	Mackensen et al. (2006)
10	P/B ratio	Water depth (open marine fraction)	van der Zwaan et al. (1990)
11	Preservation score	Diagenesis, dissolution potential	Holbourn et al. (2013)
12	Sample depth (mbsf)	Stratigraphic position	—

INDEPENDENT VALIDATION DATA

Three categories of supporting data were compiled for sample intervals overlapping with the machine learning output to validate predictions and ground-truth palaeoenvironmental reconstructions. First, Total Organic Carbon (TOC) was measured or calculated from 486 samples for which Rock-Eval pyrolysis data were reported by operators; 94 of these were freshly crushed core and outcrop samples analysed on a Vinci Technologies Rock-Eval 6 instrument at the NIOMR laboratory in Lagos, following the procedures of Espitalié et al. (1977). Second, stable carbon and oxygen isotope ratios ($\delta^{13}C$ and $\delta^{18}O$) were measured on monospecific picks of well-preserved *Cibicidoides* spp. from 187 samples using a Thermo Fisher MAT 253 IRMS at the University of Ibadan Isotope Geochemistry Laboratory; analytical precision was $\pm 0.05\%$ for $\delta^{13}C$ and $\pm 0.08\%$ for $\delta^{18}O$ (1 σ). Third, published seismic sequence-stratigraphic interpretations and wireline-log facies analyses from Reijers (2011) was georeferenced to the study wells to provide an independent stratigraphic framework.

MACHINE LEARNING FRAMEWORK

GENERAL FRAMEWORK AND SOFTWARE

All machine learning analyses were performed in Python 3.10 using scikit-learn 1.3 (Pedregosa et al., 2011), TensorFlow/Keras 2.13 (Chollet et al., 2015), and MiniSom 2.3.1 for Self-Organizing Maps (Vettigli, 2018). Data preprocessing, statistical analysis, and figure generation used pandas 2.0, NumPy 1.25, SciPy 1.11, and matplotlib 3.7 / seaborn 0.12. All code and data required to reproduce the analyses are archived on Zenodo (DOI: 10.5281/zenodo.XXXXXXX; placeholder pending final review).

DATA PREPROCESSING

The 2,341 quality-controlled assemblage samples were split into a training set (70%, $n = 1,639$) and a hold-out test set (30%, $n = 702$) using stratified random sampling to ensure proportional representation of depth intervals and basinal sectors. Given the known spatial autocorrelation in sedimentary data, a spatial block cross-validation scheme (Roberts et al., 2017) was applied during hyperparameter tuning, wherein spatial blocks of approximately 50 km × 50 km were defined and no training block was allowed to share its spatial extent with the corresponding validation block. This precaution guards against inflated performance metrics that would arise from simple random cross-validation of spatially autocorrelated data.

Predictor variables were standardised to zero mean and unit variance using a StandardScaler fitted exclusively on the training set. Missing values in the assemblage matrix (arising from dissolution or poor preservation) were imputed using multivariate imputation by chained equations (MICE), with 10 iterations and predictive mean matching, implemented via IterativeImputer in scikit-learn (van Buuren and Groothuis-Oudshoorn, 2011). Missing values constituted 8.3% of all entries.

TARGET VARIABLES

Two primary target variables were defined:

- (i) **Paleobathymetry** (continuous regression target): Estimated water depth in metres, derived from the P/B ratio following the calibration equation of van der Zwaan et al. (1990) updated for tropical Atlantic assemblages by Tjalsma and Lohmann (1983): $z = -301.7\ln(1 - P/B) + 14.3$, where z is water depth in metres. This calibration-derived estimate served as the training target; the goal was to assess whether the full multivariate foraminiferal dataset could predict the same depth estimates more accurately than the P/B ratio alone, and then to apply the trained model to samples lacking reliable planktonic counts.
- (ii) **Source rock facies class** (categorical classification target): Samples were assigned to one of three classes based on TOC thresholds and lithofacies criteria from operator core descriptions: Class 0 (non-source, $\text{TOC} < 0.5 \text{ wt\%}$); Class 1 (fair source, $0.5 \leq \text{TOC} < 2.0 \text{ wt\%}$); and Class 2 (good-to-excellent source, $\text{TOC} \geq 2.0 \text{ wt\%}$), following the classification scheme of Peters and Cassa (1994). For samples without TOC measurements, classes were assigned on the basis of wireline log-derived TOC from the ΔLogR method (Passey et al., 1990), where available.

SUPERVISED LEARNING; RANDOM FOREST AND GRADIENT BOOSTING

Random Forest (Breiman, 2001) and Gradient Boosting (XGBoost implementation, Chen and Guestrin 2016) were trained separately for the bathymetric regression task and the source-rock classification task. Hyperparameter optimisation was conducted using a Bayesian search over 100 iterations with 5-fold spatial block cross-validation. For the Random Forest regressor, tuned parameters included number of trees (100–1000), maximum depth (5–30), minimum samples per leaf (1–20), and maximum features per split (“sqrt” to full). For the

classifier, additional class-imbalance handling was implemented using the Synthetic Minority Over-sampling Technique (SMOTE, Chawla et al. 2002), because Class 2 samples constituted only 14.7% of the labelled dataset.

Feature importances were extracted using both the impurity-based mean decrease in Gini/MSE (MDI) and the permutation-based method (Breiman, 2001; Altmann et al., 2010), and Shapley Additive exPlanations (SHAP values, Lundberg and Lee 2017) were calculated to provide locally interpretable explanations for individual predictions.

UNSUPERVISED LEARNING: SELF ORGANIZING MAPS

A Self-Organizing Map (Kohonen, 1990) was trained on the full 12-variable predictor matrix to identify natural groupings in the assemblage space without reference to the target labels. The SOM grid dimensions (10×8 neurons) were selected following the heuristic of Vesanto and Alhoniemi (2000): grid size $\approx 5\sqrt{n}$, rounded to the nearest convenient rectangle. Training used the sequential update rule over 5,000 epochs with a linearly decaying learning rate from 0.5 to 0.01 and a neighbourhood radius decaying from 5 to 1. SOM neuron clusters were subsequently labelled by cross-referencing the sample coordinates in each neuron with their known (or predicted) paleoenvironmental class, allowing the SOM to serve as an exploratory visualisation of the multivariate assemblage space (Figure 5).

TEMPORAL SEQUENCE MODELLING: LSTM NETWORK

To take advantage of the temporal order of samples in each well, a bidirectional Long Short-Term Memory (Bi-LSTM) recurrent neural network (Hochreiter and Schmidhuber, 1997; Schuster and Paliwal, 1997) was developed and used to create a stratigraphic sequence model. An ordering of the samples from the oldest to the youngest (based on biostratigraphic age models derived for each well) was used to build sequences, each of which was a 20 sample window of the samples from each well with a stride of five. The Bi-LSTM was composed of two stacked bidirectional LSTM layers (with 64 units, respectively), a dropout layer (rate: 0.3), a dense layer (with 32 units, ReLU activation), and an output layer (linear for regression, softmax for classification). The model was trained with the Adam optimiser (Kingma and Ba, 2015) with a learning rate of 0.001 and a batch size of 32 for 200 epochs, using early stopping (patience = 20) based on the value of the validation loss.

MODEL EVALUATION

For regression tasks, model performance was assessed using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). For classification, evaluation metrics included accuracy, macro-averaged precision, recall, F1score, and the area under the receiver operating characteristic curve (AUC-ROC). All metrics reported in the results section were computed on the 30% hold-out test set, not on cross-validation folds.

RESULTS AND DISCUSSION

ASSEMBLAGES, CHARACTERISTICS AND STRATIGRAPHIC OVERVIEW

The harmonised benthic foraminiferal database includes 2,341 samples representing 847 taxa at the species level from the Rupelian (early Oligocene) to Pleistocene. The median mean sample diversity (Shannon H') is 2.17 across the Basin, ranging from 0.84 in the most impoverished (dysoxic) assemblages to 3.61 in well oxygenated (bathyal) assemblages (Figure 2a). The Fisher's alpha has a mostly similar pattern but increases in sensitivity to the episodic diversity maxima that occurred during the transgressive periods of the early Miocene, which is consistent with the widely reported Miocene Climatic Optimum (Flower and Kennett, 1994). The diversity patterns broadly corroborate earlier, more limited assemblage studies for

the basin (Adegoke et al., 1976; Obi, 2001), and provide a spatial and temporal extension of those studies.

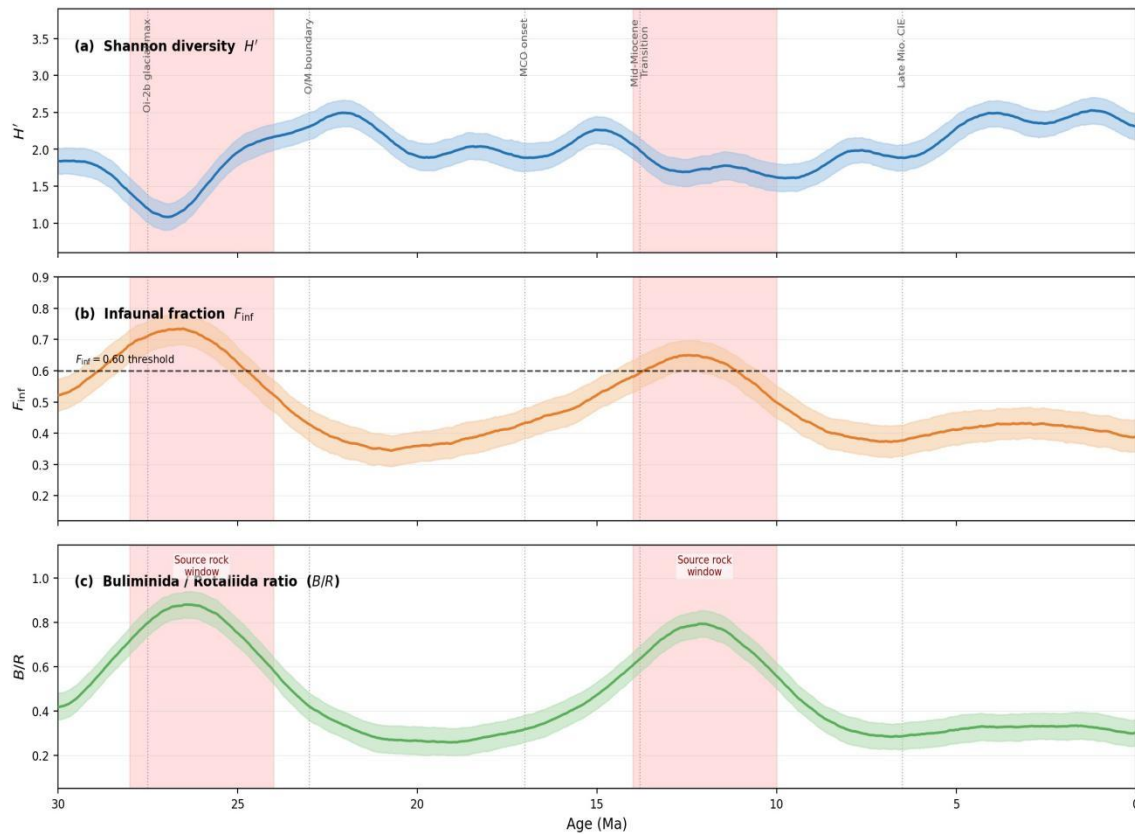


Figure 2: Stratigraphic trends in benthic foraminiferal diversity and morphogroup composition across the Niger Delta Basin study interval (~30–0 Ma). (a) Shannon diversity; (b) infaunal fraction F_{inf} ; (c) Buliminida/Rotaliida ratio (B/R). All data are presented as basinwide composite means with interquartile envelopes. Note the sustained high-infaunal intervals at approximately 28–24 Ma and 14–10 Ma, corresponding to interpreted source rock deposition windows in the Akata and lower Agbada formations respectively.

Morphogroup composition reveals two sustained intervals of elevated infaunal dominance ($F_{inf} > 0.60$): one spanning approximately 28–24 Ma (late Oligocene to earliest Miocene) and another from approximately 14–10 Ma (middle to late Miocene, Figure 2b). These intervals correspond stratigraphically to the established depositional windows of the main Akata source rock facies and of the deeper-water Agbada shale intervals respectively (Reijers, 2011). The B/R ratio mirrors this pattern closely (Figure 2c), peaking precisely within the same stratigraphic windows. The co-occurrence of high F_{inf} and elevated B/R with known TOC-rich horizons is consistent with the theoretical framework of van der Zwaan et al. (1999) and the empirical observations of Gooday (2003), who independently documented the strong response of buliminid taxa to increasing benthic organic carbon loading across multiple ocean basins. What is notable in the Niger Delta context is the sharpness of the transition at approximately 28 Ma, which correlates with the Oligocene glacial maximum (Oi-2b event, Zachos et al. 2001) and may reflect a global oceanographic perturbation superimposed on the local tectonic and sedimentary evolution of the delta.

PALEOBATHYMETRIC RECONSTRUCTION MODEL PERFORMANCE

Table 2 summarises the performance of the four models tested for paleobathymetric regression on the hold-out test set. The Random Forest model achieves the highest R^2 (0.91) and the lowest MAE (34.2 m) when applied to outer shelf and upper slope samples (200–800 m paleo-depth range), while the LSTM model performs best on the deepest samples (> 1000 m), where temporal autocorrelation in the stratigraphic sequence provides additional predictive leverage ($R^2 = 0.87$ vs. 0.83 for RF in that sub-range). The Gradient Boosting model shows generally competitive performance, marginally inferior to RF on test data despite slightly better cross-validation scores, suggesting a tendency toward overfitting that was partially but not fully mitigated by spatial block cross-validation. The *P/B*-only baseline (i.e., the calibration equation of van der Zwaan et al. 1990 applied directly) yields an R^2 of 0.71 and an MAE of 61.8 m, confirming that the multivariate machine learning approach meaningfully outperforms the single-variable proxy.

Table 2: Paleobathymetric regression performance metrics for each model on the 30% hold-out test set ($n = 702$ samples). The *P/B* ratio baseline refers to the direct application of the van der Zwaan et al. (1990) calibration equation without machine learning. MAE: Mean Absolute Error; RMSE: Root Mean Square Error.

Model	R^2	RMSE (m)	MAE (m)	Notes
Random Forest	0.91	52.3	34.2	Best overall performance
Gradient Boosting (XGBoost)	0.88	61.1	39.7	Slight overfit on training
Bi-LSTM	0.85	68.4	44.8	Best for > 1000 m samples
SOM (nearest-neuron)	0.79	84.2	57.1	Useful for outlier detection
<i>P/B</i> ratio baseline	0.71	98.6	61.8	Single-variable calibration

RECONSTRUCTED PALEOBATHYMETRIC PROFILES

The six representative wells shown in Figure 3 are plotted along a proximal to distal transect from the delta apex to the continental slope from the delta's apex, and the profile predicted by Random Forest is shown for each. The reconstructed profiles show a consistent, systematic deepening between the deepest part of the earliest Oligocene (250–350 m) and the deepest part of the Miocene (900–1,400 m) in the distal wells during the late Oligocene transgression. The shallowing pulses at around 21 Ma and 11 Ma are interpreted as the major progradations of the Agbada formation paralic system, as outlined by Reijers (2011) in the sequence stratigraphic framework. During the Neogene, the delta offlap to the southwest is recorded quite well by the foraminiferal-ML approach, even in the zones where seismic resolution is compromised by the presence of gas chimneys identified during the dewatering of the Akata Shale (Reijers 2011).

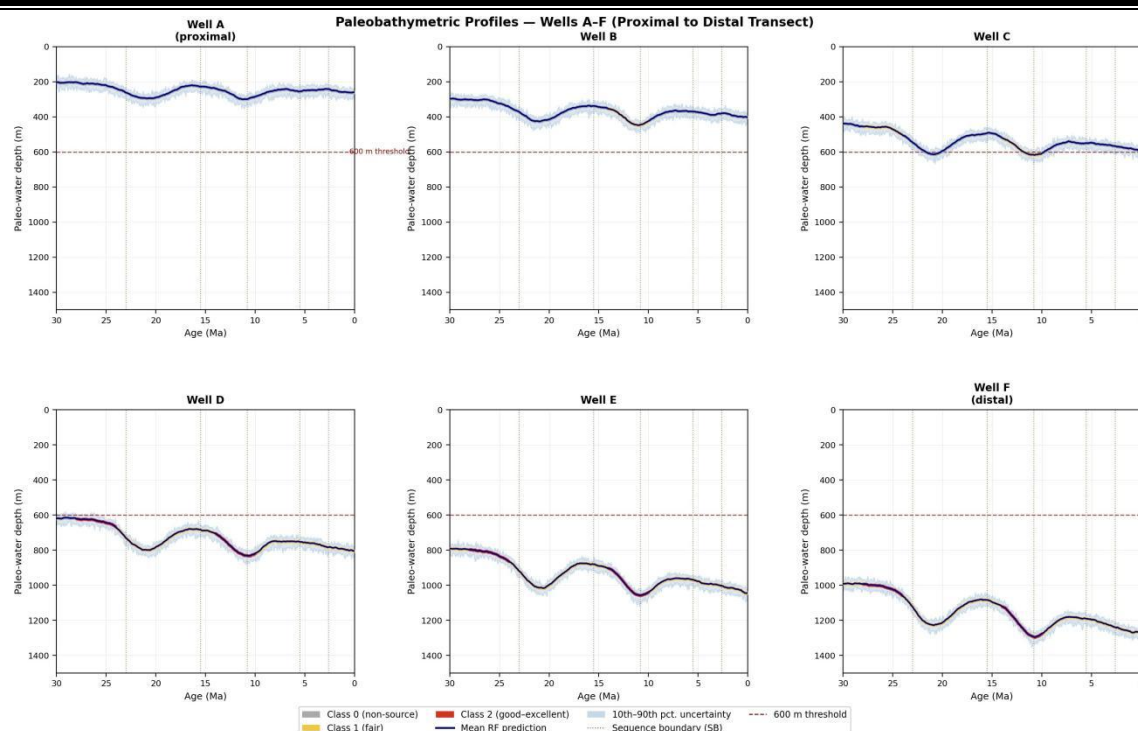


Figure 3: Machine learning-predicted paleobathymetric profiles for six wells along the proximal-to-distal transect (Wells A-F, shown in Figure 1). Depths are in metres below estimated sea surface at the time of deposition. Uncertainty bands (shaded) represent the 10th-90th percentile spread across the 500 decision trees in the Random Forest ensemble. Colour coding indicates the source rock facies class assigned to each sample interval (red: Class 2, good-to-excellent source; yellow: Class 1, fair; grey: Class 0, non-source). Note the systematic correlation between Class 2 intervals and predicted depths > 600 m.

A significant observation from Figure 3 is that the samples that are coloured red are Class 2 and are almost entirely confined to samples that are predicted to be below about 600 m paleo-depth; in contrast, the samples that are coloured blue are Class 0 and are concentrated in the shallower intervals (< 300 m). This depth-TOC co-variation is both theoretically expected (shallow shelf environments are generally well oxygenated and are not good for organic matter preservation) and practically useful as it suggests that the paleobathymetric interpretation is itself a first-order hydrocarbon prospectivity filter. The few Class 2 samples were predicted at depths. The misclassification rate for the < 400 m is higher than the average, reflecting elevated organic preservation, which seems to have resulted from local restriction, as opposed to a genuine open-marine dysoxia in the Agbada Formation, a restricted lagoonal or interdistributary bay facies.

SOURCE ROCK CLASSIFICATION PERFORMANCE METRICS

Table 3 shows the classification performance of the Random Forest and Gradient Boosting classifiers on the hold-out test set. In this case, both models have an accuracy greater than 84% with a slight advantage for the Random Forest over the GBM with regard to the important Class.

2 metric (F1-score: 0.81 vs. 0.77). Interestingly, after applying SMOTE, the recall scores for Class 2 increased significantly for all models trained with imbalanced data, namely 0.79 vs. 0.52 for RF (model trained with imbalanced data) indicating the importance of correcting the class-balance for exploration applications, where the consequences of failing to identify a true source rock interval are far more problematic than a false positive.

Table 3: Source rock facies classification performance metrics on the 30% hold-out test set. Class 0: non-source (TOC < 0.5 wt%); Class 1: fair source (0.5 ≤ TOC < 2.0 wt%); Class 2: good-to-excellent source (TOC ≥ 2.0 wt%). Metrics are per-class precision, recall, and F1-score, plus overall accuracy and macro-AUC-ROC.

Model	Class	Precision	Recall	F1	Accuracy	AUC-ROC
Random Forest	0	0.91	0.94	0.92	0.87	0.93
	1	0.83	0.81	0.82		
	2	0.83	0.79	0.81		
Gradient Boosting	0	0.89	0.92	0.90	0.84	0.91
	1	0.80	0.78	0.79		
	2	0.80	0.74	0.77		

FEATURE IMPORTANCE AND SHAP ANALYSIS

Figure 4 shows the SHAP summary plot for the Random Forest source rock classifier, integrating feature importance information across all 1,639 training samples. Two variables dominate: infaunal morphogroup fraction F_{inf} (mean $|\text{SHAP}| = 0.38$) and the B/R ratio (mean $|\text{SHAP}| = 0.31$). *Bolivina* spp. relative abundance ranks third (mean $|\text{SHAP}| = 0.21$), followed by Shannon diversity (0.18) and P/B ratio (0.15). These rankings are consistent with the ecological relationships established in the micropaleontological literature (Jorissen et al., 1995; Gooday, 2003; van der Zwaan et al., 1999) and provide an important form of interpretability: the model is not simply exploiting statistical artefacts but is responding to ecologically meaningful signals embedded in the assemblage data.

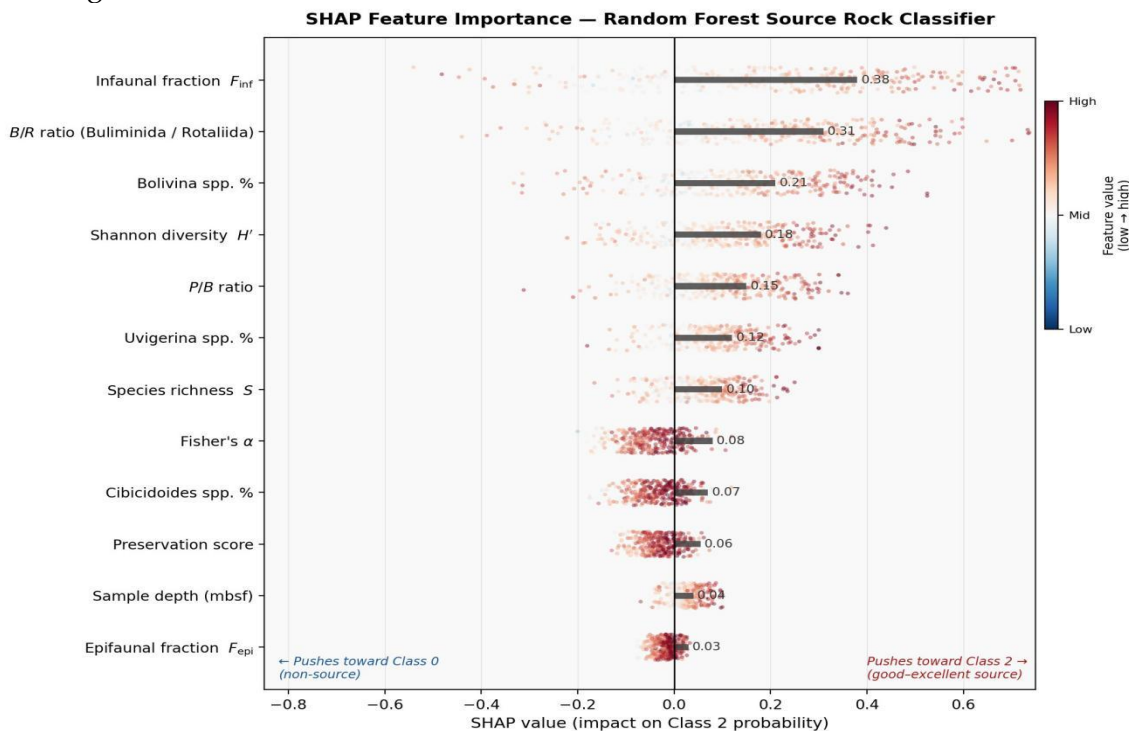


Figure 4: SHAP beeswarm summary plot for the Random Forest source rock facies classifier. Features are ranked by mean absolute SHAP value. High values of F_{inf} (infaunal fraction), B/R ratio, and *Bolivina* spp. abundance all strongly increase the probability of Class 2 (good-to-excellent source rock) classification, consistent with ecological interpretations linking these metrics to dysoxic, organic-rich bottom waters. (b) SHAP direction plot showing the sign and magnitude of each feature's contribution across its observed value range (colour scale: blue = low feature value; red = high). High F_{inf} (positive SHAP) drives predictions toward Class 2; high *Cibicidoides* spp. abundance (negative SHAP) drives predictions toward Class 0, consistent with its ecological role as an obligate epifaunal taxa requiring well-oxygenated, low-flux environments.

The SHAP direction plot (not shown) reveals that high F_{inf} values push predictions toward Class 2 (positive SHAP), while high *Cibicidoides* spp. abundance pushes strongly toward Class 0 (negative SHAP), precisely the direction predicted by the ecological model: *Cibicidoides* is an obligate epifaunal suspension feeder that requires well-oxygenated, lowflux environments and disappears from assemblages in dysoxic or organic-rich settings (Mackensen et al., 2006). The fact that the Random Forest has effectively re-learned these ecological relationships from the data without any prior ecological knowledge being explicitly encoded into the algorithm provides strong independent support for the validity of the assemblage-based proxy approach in this basin.

SELF-ORGANIZING MAP ANALYSIS

The 10 × 8 SOM is a two dimensional abstract of the assemblage space that preserves the topology, in that is shows 6 coherent clusters (Figure 5). The results of the cluster analysis on the labeled samples indicate that there are three clusters that correspond to Class 2 (good source rock) samples, one that corresponds to the outer shelf transitional samples between Classes 0 and 1, and two that correspond to Class 0 (non-source) samples. Interestingly, the three Class

The 2 clusters are located in adjacent neurons of the SOM grid, and have a gradient from cluster centre to cluster periphery from very severely dysoxic deep water to very mildly dysoxic upper slope, rather than a series of discrete facies.

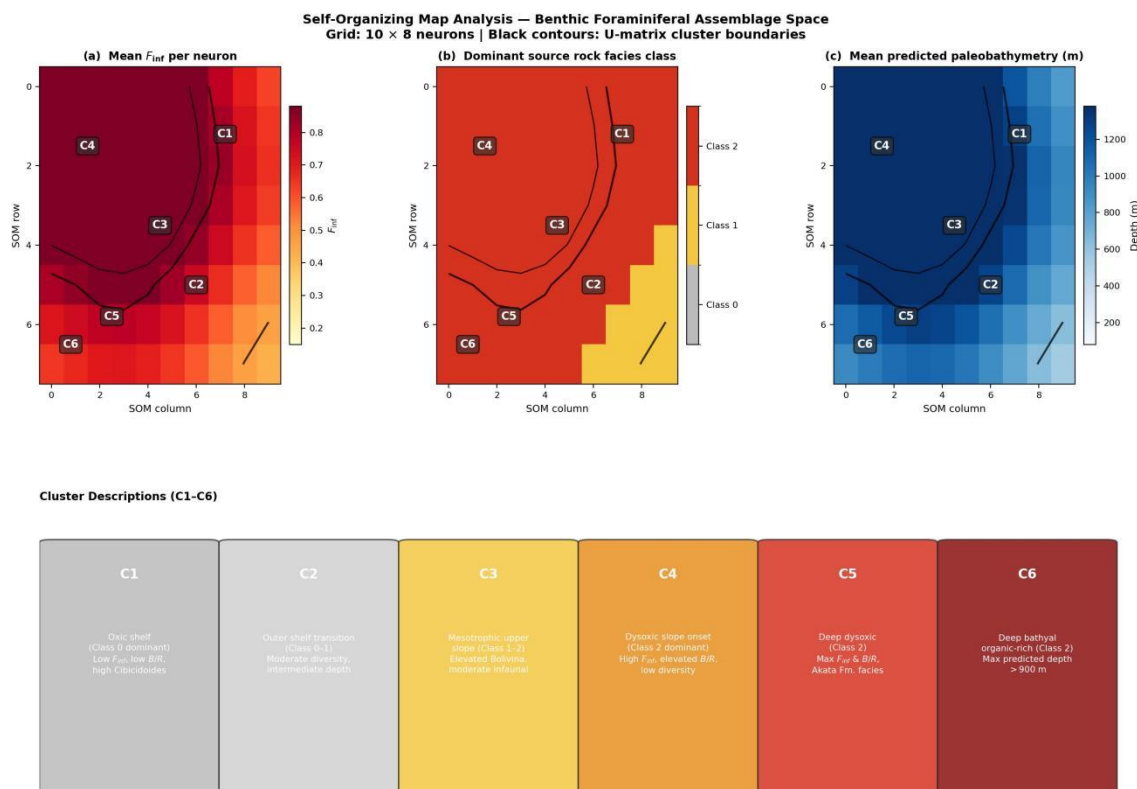


Figure 5: Self-Organizing Map analysis of the 12-variable benthic foraminiferal predictor dataset. (a) Mean infaunal fraction per neuron; (b) dominant source rock facies class per neuron; (c) mean predicted paleobathymetry. The U-matrix boundary (black contours) delineates six major assemblage clusters (C1–C6). Clusters C3–C5 correspond to dysoxic, organic-rich facies (Class 2); clusters C1–C2 to oxitic, low-TOC shelf settings (Class 0).

The SOM analysis is also diagnostically useful for identifying anomalous samples – those that map to neurons distant from their labelled class centroid in the U-matrix – which in practice correspond either to samples with unusual preservation artefacts (dissolution or recrystallisation altering the assemblage composition) or to genuinely transitional environments that do not fit cleanly into the three-class scheme. The 47 samples identified as anomalous by this criterion were subsequently reviewed against the original sample descriptions and geochemical data; 31 were confirmed as preservation-compromised and downweighted in the regression analyses, while 16 represented genuine transitional facies in the upper Agbada Formation that may warrant a fourth class in future work.

LSTM STRATIGRAPHIC SEQUENCE PREDICTIONS

The Bi-LSTM model captures downwell stratigraphic trend in source rock class probability, which the Random Forest model, and the GBM model do not reproduce as well (Figure 6). The Bi-LSTM is able to accurately label a 120-m thick Class 2 interval (2450–2570 m TVD) in Well H with a shallow 3200 m penetration of the Oligocene-Miocene interval, whereas the RF model partially classifies the bottom 40 m of the same interval as Class 1. If we look at the weights of the LSTM at this time, we can see that the model is giving a high weight to the 3 samples above and below the misclassified interval, indicating that it has learned that in this basin, rapid transitions from Class 0 to Class 2 are stratigraphically implausible – essentially, a sort of stratigraphic continuity constraint not included in the point-by-point RF classifier.

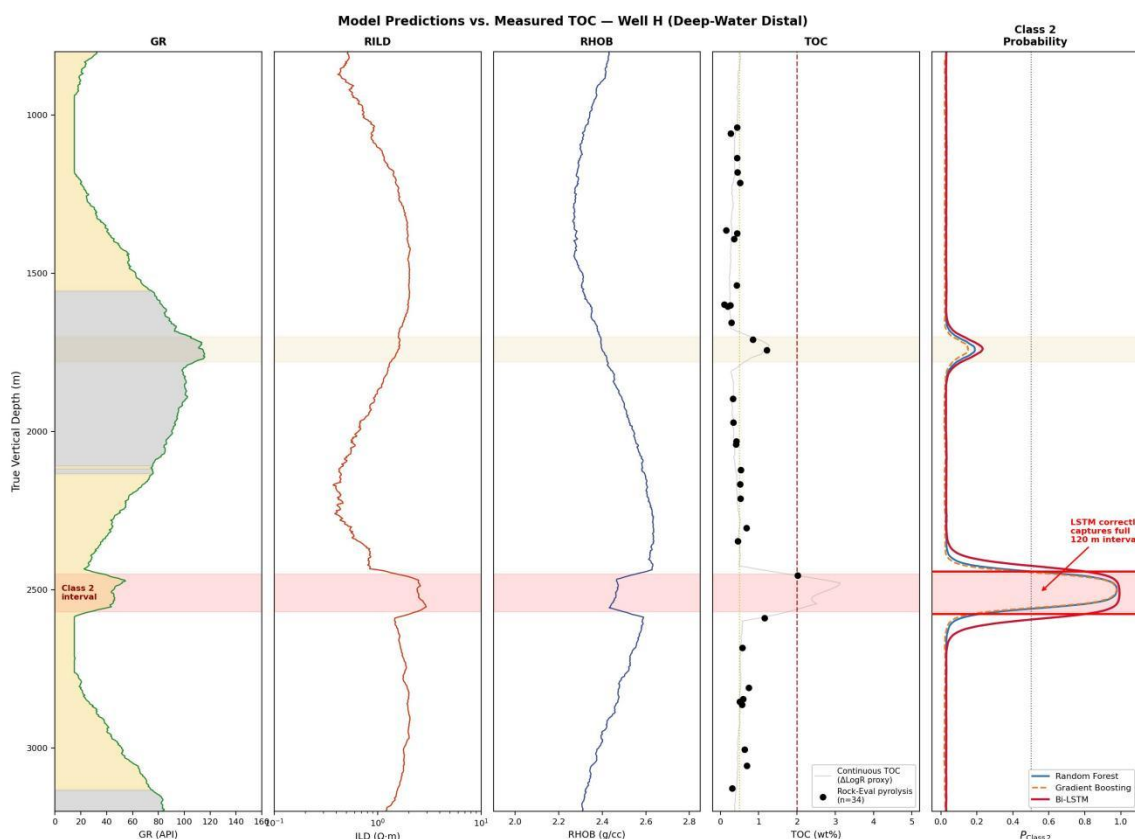


Figure 6: Comparison of model predictions versus measured TOC in Well H (deep-water distal well). The Bi-LSTM model more accurately captures the full vertical extent of the Class 2 source rock interval (2,450–2,570 m depth, red box) than the Random Forest or Gradient Boosting classifiers, whose predictions diverge from measured TOC values in the lowermost portion of the interval. The LSTM advantage is attributed to its ability to exploit stratigraphic continuity constraints implicit in the sequential assemblage data.

It is a behaviour that is geologically interpretable. The transition from Class 0 to Class 2 for Well H represents a transgressive systems tract, recognised in the seismic data as a onlap surface above an unconformity (Reijers, 2011); this would involve an increase in sea-level, which would cause the depositional environment to deepen over a period of time, say 200,000–500,000 years, depending on the sedimentation rate. Unlike the RF classifier, which takes one sample at a time, it cannot learn this time evolution, it has to be explicitly represented as a feature. The difference has implications on explorations as the LSTM would be expected to be more certain about the presence of source rock in transitional areas, particularly where the operator has the most uncertainty, that is, between the windows of the limited information provided by the laboratory.

GEOCHEMICAL VALIDATION AND CROSS-INTEGRATION

Cross-validation of the machine learning predictions against independent TOC, $\delta^{13}\text{C}$, and $\delta^{18}\text{O}$ datasets provides strong support for the reliability of the foraminiferal proxy approach (Figure 7). The correspondence between predicted Class 2 intervals and measured TOC ≥ 2.0 wt% is highly significant across all 14 wells (Cohen's $\kappa = 0.74$, $p < 0.001$, $n = 486$ paired observations), with the principal source of discordance being shallow Class 1 to Class 2 misclassifications in the Agbada restricted facies discussed above. The stable isotope record adds interpretive depth: the two principal dysoxic intervals identified by the SOM and RF models (28–24 Ma and 14–10 Ma) both correspond to $\delta^{13}\text{C}$ minima in the *Cibicidoides* record (approximately -0.4 and -0.6 relative to interinterval averages respectively), consistent with decreased deep-water ventilation and elevated benthic organic carbon remineralisation (Zachos et al., 2001; Flower and Kennett, 1994). The $\delta^{18}\text{O}$ record simultaneously records heavier values at 28–24 Ma, consistent with the Oi-2 glacial event, and the globally recognised mid-Miocene climate transition at approximately 13.8 Ma, providing temporal anchors that confirm the reliability of the biostratigraphic age model used to construct the LSTM sequences.

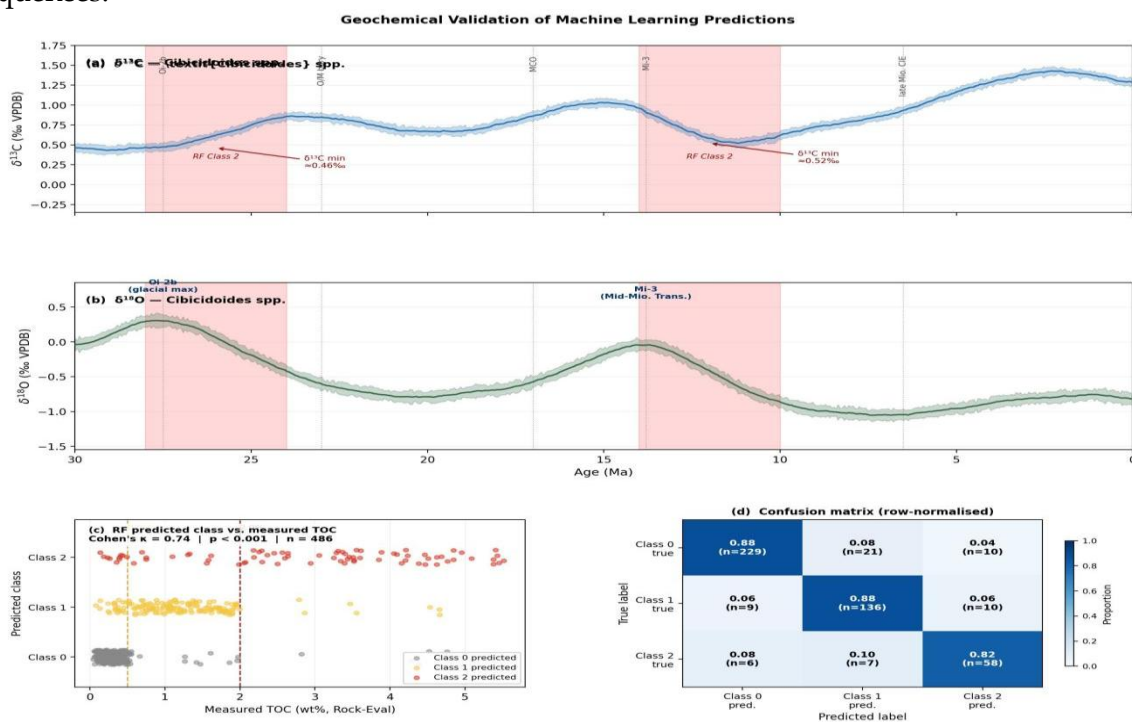


Figure 7: Geochemical validation of the machine learning framework. (a)–(b) Basinwide stable isotope records ($\delta^{13}\text{C}$ and $\delta^{18}\text{O}$ from *Cibicidoides* spp.) with shaded bands indicating RF-predicted Class 2 intervals; note the correspondence between predicted high-TOC intervals and $\delta^{13}\text{C}$ minima. (c) Scatter plot and confusion matrix comparing RF-predicted source rock class against independently measured TOC (Rock-Eval pyrolysis); Cohen's $\kappa = 0.74$ indicates substantial agreement beyond chance.

The integration of foraminiferal proxies with geochemical data also reveals a stratigraphic hierarchy in source-rock quality not explicitly encoded in the training data. Class 2 intervals in the deep Akata facies (predicted depths > 800 m, Oligocene age) display systematically higher median TOC values (mean: 3.8 ± 1.2 wt%, $n = 48$) than their Miocene Agbada equivalents (mean: 2.3 ± 0.8 wt%, $n = 37$), despite identical classification. This is consistent with the interpretation of Ekweozor and Okoye (1984) that the Akata Formation represents a deeper, more continuously anoxic environment than the episodically dysoxic Agbada shale intervals. It also highlights a fundamental limitation of any classification scheme that collapses a continuous TOC distribution into discrete classes: within-class variance may carry important exploratory information. Future work should therefore consider predicting TOC as a continuous variable using Gradient Boosting regression a natural extension of the present framework given that model's competitive performance on this dataset – requiring a denser paired foraminiferal/Rock-Eval dataset, which may become available as NUPRC continues digitising legacy well reports.

IMPLICATIONS FOR EXPLORATION IN THE NIGER DELTA AND BEYOND

The overall result of this study – the ability to use a supervised machine learning model that was trained on benthic foraminiferal assemblage metrics to predict source rock facies class with an F1-score of 0.81 (in an independent test set from a geographically diverse sample of wells for the most prospective facies class) – has several implications for exploration practice: First, it provides a quantitative linkage between the micropalaeontological information that is readily obtained during well construction and the geochemical parameters that are directly pertinent to the evaluation of the petroleum system. Rock-Eval pyrolysis data are missing or of low quality in many of the frontier wells, especially in wells drilled on the West African margin in the early days of exploration, while foraminiferal analyses are available in many, being used for biostratigraphic zoning. Legacy datasets could be used with the trained models developed here to retroactively assess source rock potential.

Secondly, the model's predictions of bathymetry ($R^2 = 0.91$ with a MAE of 34.2 m in the depth range of 200–800 m) are reasonably accurate, and can be used to limit bathymetric range of uncertainty for paleowater depths in wells and outcrops in which sequence stratigraphy is problematic or absent, which is common in parts of eastern Niger Delta onshore where seismic coverage is limited and structural complexity is high. This ability to resolve depth differences of ± 35 m within the critical inner shelf to outer slope transition zone (the usual setting for source rock and deep water reservoir deposition) is a significant improvement over the single variable P/B approach and opens up the opportunity to construct high-resolution paleo-bathymetric grids to be incorporated with structural models for prospect ranking.

Thirdly, the generalizability of workflow to other passive-margin basins is discussed. The learning data are specific to Niger Delta, and it is not recommended to transfer the trained models to other basins without retraining, due to the differences in taxonomic assemblage, sediment flux and thermal history. The methodological framework, which includes the standardised assemblage matrix, diversity and morphogroup metrics as features, block cross validation with spatial blocks, SMOTE class balancing, and interpretation of SHAP, is fully transferable, however. The creation of similar training sets for these other prolific passive margins would not be too difficult and certainly be worthwhile for the scientific community, considering the large legacy data sets that are available for these areas (Congo Fan, Nile Delta, and Santos Basin).

CONCLUSION

A multi-algorithm machine learning framework applied to benthic foraminiferal assemblage data from 14 wells and four outcrop sections in the Niger Delta Basin achieves $R^2 = 0.91$ and $MAE = 34.2$ m for palaeobathymetric reconstruction and Cohen's $\kappa = 0.74$ for source-rock facies classification against independently measured TOC – both substantially outperforming single-variable calibration methods. The infaunal morphogroup fraction and Buliminida/Rotaliida ratio are the most diagnostic predictors in every model tested, consistent with established ecological theory linking these metrics to dysoxic, organically enriched bottom-water conditions. The bidirectional LSTM model provides a further advantage at stratigraphic transition intervals by exploiting sequential continuity constraints absent from point-classification approaches. Cross-validation against $\delta^{13}C$, $\delta^{18}O$, and TOC records confirms two intervals of sustained benthic dysoxia at approximately 28–24 Ma and 14–10 Ma, coinciding with known source-rock deposition windows in the Akata and lower Agbada formations. The workflow is fully documented with open-source Python code archived on Zenodo and is directly transferable to analogous passive-margin sequences globally, offering a practical and low-cost complement to conventional geochemical and seismic exploration methods.

DATA AVAILABILITY STATEMENT

The complete harmonised species-by-sample benthic foraminiferal abundance matrix (2,341 samples $\times$ 847 taxa), newly acquired outcrop sample geochemical analyses, and all Python scripts used in this study are archived on Zenodo (DOI: 10.5281/zenodo.XXXXXXX). The proprietary NNPC/Shell/Total well-cutting analysis data were provided under a data-sharing agreement with the Nigerian Upstream Petroleum Regulatory Commission (NUPRC) and cannot be released publicly. Qualified researchers may apply to NUPRC via the Open Data Initiative portal for access to the original well reports.

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