



Utilizing Probabilistic Neural Network for Reservoir Assessment: A Case Study from an Onshore Niger Delta Field

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Abstract

Accurate reservoir characterization is often useful in defining the boundaries of prospective oil or gas fields as well as in lessening the likelihood of drilling ineffective wells. Identifying fluid and lithology in heterogeneous and complex reservoirs, such as those found in the Niger Delta, is a difficult task. However, conventional seismic attributes cannot easily characterize such heterogeneous and complex reservoirs. It is critical to understand the complexities of reservoir characteristics and associated uncertainties using integrated multisource data and more robust approaches. Consequently, this piece of work is aimed at characterising the reservoir 3D water saturation volume by employing the probabilistic neural network (PNN) analysis of full-stack seismic data and water saturation logs. In this case study, two reservoirs from the onshore Niger Delta's Sigma field were set aside for characterization.

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A high-resolution saturation volume was predicted using well log measurement and the results produced tremendous outcomes. The predicted water saturation volume and the actual saturation logs had a 0.90 normalized correlation. The outcomes validate the ability of the workflow to precisely forecast water saturation at a greater resolution.

Key words: PNN, reservoir characterisation; deterministic inversion; water saturation.

1.0 Introduction

Due to the limitations of seismic resolution, characterizing high-resolution reservoirs has always been challenging. This endeavour is all the more crucial given that heterogeneous and deep-water turbidite reservoirs in the Niger Delta are frequently varied and complex. These reservoirs are distinguished by a high degree of sand thickness and quality variability. Additional common difficulties in describing Niger Delta reservoirs include uncertainties regarding the lateral extent, pinchout, distribution of the reservoir characteristics (such as fluid type, fluid saturation, net pay thickness, and porosity, etc.) and fault

placements along the reservoirs (Inichinbia *et al.*, 2014, Horsfall *et al.*, 2017, Okeugo *et al.*, 2018). Previous studies have shown that inadequate reservoir characteristics has led to drilling up of dry wells or fast drying up wells or low oil recovery or even abandoning a field (Ekanem *et al.*, 2021).

This study seeks to solve the problem by utilizing new methods for analyzing seismic data through enhanced interpretation strategies. Recently, neural network methods have been used to solve geophysical difficulties by reducing the inaccuracy in predictions and processes. Using data from numerous wells and seismic data, it trains a neural network to predict features independent of the well control. Given their ability to solve for multiple variables simultaneously and their ability to perform the extremely sophisticated statistical analysis needed to get a prediction of lithology from enormous seismic data volumes, neural networks are well adapted to geosciences challenges. They were originally designed as a technique to simulate how the human brain functions. These methods have moved out of the research lab and into commercial application, even as research into the original human neural pathway continues. A PNN is a computer programme that may be trained to learn and generalize the complicated, nonlinear rules and relationships that control a set of data inputs and related outputs. PNNs are a different type of technology that can be used to solve seismic issues.

When the inversion's outputs are added to the standard seismic properties used in network training, neural network analysis can greatly improve the seismic inversion outcome (Mohamed *et al.*, 2014, Mohamed *et al.*, 2015, Mohamed *et al.*, 2019). Two benefits of neural networks include their ability to handle nonlinearity and the absence of deterministic model procedures at the start of the trial. In an n-dimensional vector field covering the whole

3D input seismic attributes data set, the network is able to freely explore, recognize, and categorize patterns as well as map similar multi-attribute replies onto suitable log-property responses. In the current survey, petrophysical properties (water saturation) that can resolve nonlinear interactions were estimated using the PNN technique. A nonlinear relationship between seismic features and well-log attributes can be established using a neural network technique. This relationship is utilized to determine the well-log property at every position across the seismic data using external pre-stack inverted elastic attributes as well as sample-based internal seismic (instantaneous, windowed frequency, filters, derivatives, integrated, and temporal) attributes. In this present study, the seismic full-stack data was utilized to forecast S_w using the PNN approach and its internal attributes. The primary aim of this work is to improve reservoir characterization by forecasting 3D high-resolution water saturation in a Niger Delta field.

2.0 Geologic setting of the study area

The Sigma field is located in the eastern Coastal Swamp depobelt, a local sub-basin of the onshore Niger Delta Basin, which is situated in the Gulf of Guinea on the edge of West Africa (Fig. 1a, b). The Cameroon Volcanic Line in the east, the Dahomey Basin in the west, and the 4000 m bathymetric contour in the south serve as the limits of the Niger Delta Basin (Onuoha, 1999). A failed arm of a rift (connected to the opening of the South Atlantic in the Early Jurassic-Cretaceous) that the rifting stopped in the Late Cretaceous correlates to the Niger Delta Basin, which is located at the southern end of the Benue Trough (Lehner *et al.*, 1977). The Early Cretaceous subsidence of the African Continental edge and deposition of clastic materials resulted in the formation of two arms of a triple junction consisting of the collapsed South Atlantic margin, which gave rise to the

Niger Delta (Edwards, 2000; Akpan *et al.*, 2020a).

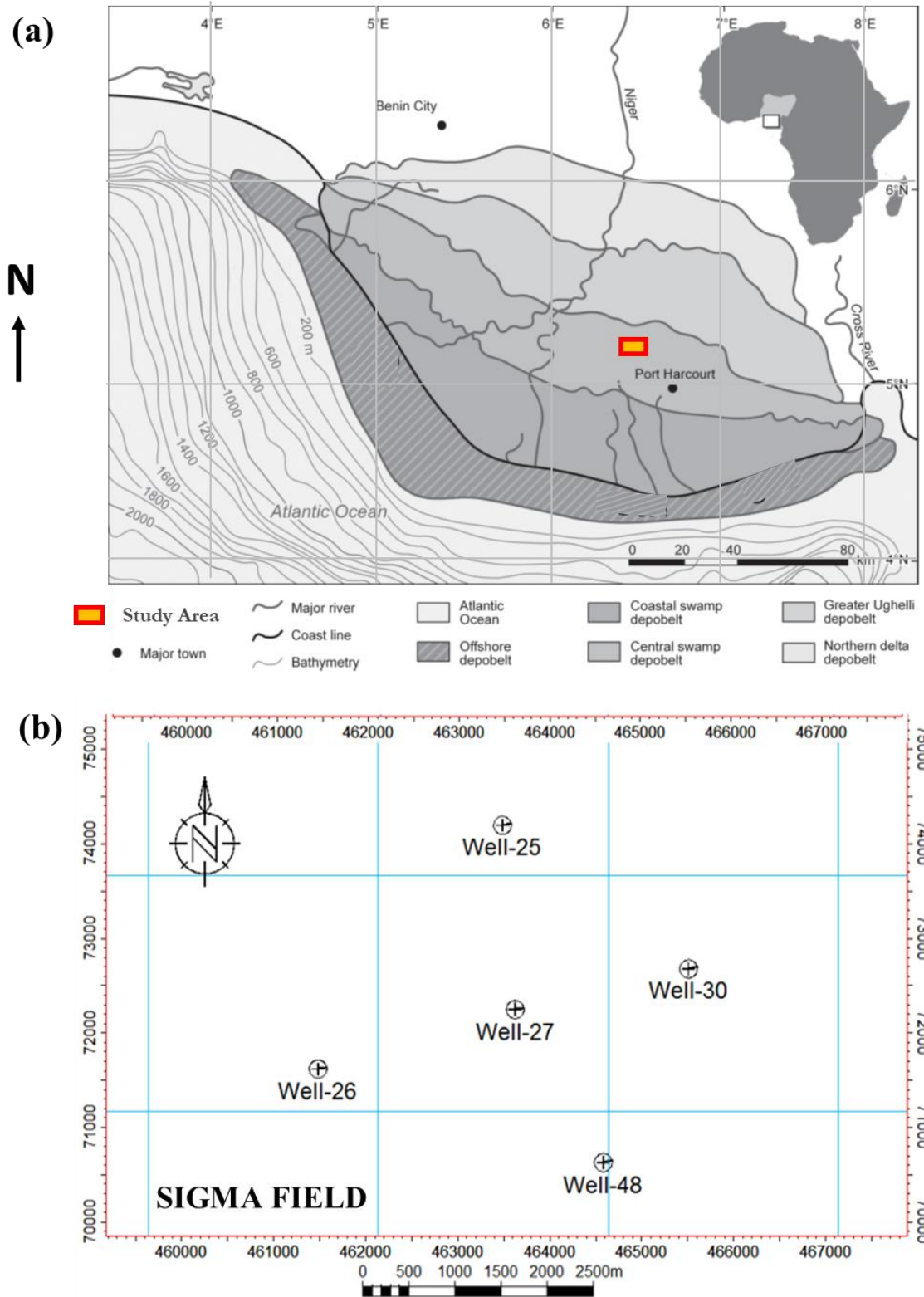


Figure 1: (a) Map of the Niger Delta showing the various depositional belts and the study area (after Adojoh *et al.*, 2017). (b) Well bore location and distribution across the study area

When sediments mostly sourced from the weathering flanks of the Niger-Benue drainage system started to build out beyond troughs between basement horst blocks at the northern flank of the current delta area during the Late Paleocene/Eocene, the basin formed as a result of the creation of a delta (Doust *et al.*, 1990, Stacher, 1994). Pre- and syn-sedimentary tectonics related to the interaction between rates of sediment supply and subsidence has shaped the basin's structures and strata (Ejedawe, 1981, Knox and Omatsola, 1987, Stacher, 1995).

A Cenozoic clastic association with an upward-coarsening regressive association makes up the geologic sequence of the Niger Delta Basin. Three lithostratigraphic units make up this sequence, which can be up to 12,000 m (39,370 ft) thick. The source and reservoir rocks are interstratified marine shales of the Akata Formation, paralic sandstones, siltstones, and shales of the Agbada Formation, and continental alluvial sands and clays of the Benin Formation, which are all diachronous (Short and Stauble, 1976; Ekweozor and Daukoru, 1984; Akpan *et al.*, 2020b; Ekanem *et al.*, 2022a, b). These are deep, intricate Sedimentary Formations that were quickly deposited during intense fluvio-deltaic-eustatic sea level fluctuations. The surface upon which sedimentary layers were produced is underlain by thick, poorly compacted, unstable mobile shales of the Akata Formation that produce a complex series of gliding surfaces and depobelts. Deposition inside the depobelts is controlled by large contemporaneous glide-plane extensional faults and folds (Fig. 1a). Shale diapirs, roll-over anticlines, collapsed growth fault crests, back-to-back structures, and steeply dipping, closely spaced flank faults are structural features in the Niger Delta Basin that provide good migratory paths and entrapment mechanisms for hydrocarbon accumulation (Evamy *et al.*, 1978; Xiao and Suppe, 1992; Dim and Onuoha, 2017; Akpan *et al.*, 2022).

The hydrocarbon reservoirs often thicken toward the down-thrown sides of growth faults, with thicknesses ranging from less than 14 meters (45 feet) to a few feet with thicknesses larger than 46 meters (150 feet) (Weber and Daukoru, 1975). According to Kulke, (1995), spiking bars of channels distribute along the coastal barrier bars, which are intermittently cut by channels that are sand-filled within the delta front. These channels constitute the most key reservoir entities in Niger the Basin.

3.0 Theoretical Basis

The PNN is a theory of Bayes-Parzen classification, which is based on neural network principle (Moheballi *et al.*, 2020). It employs Gaussian weighting functions in fitting the seismic attributes (x) to the chosen training samples (x_i). The mean of a normal Gaussian distribution is a representation of the training sample in which the algorithm can find the best smoothing parameter σ_j or standard deviation. The basic equation for the general PNN regression according to Todorov (2000) is given by the expression:

$$y'(x) = \frac{\sum_{i=1}^n y_i \exp(-D(x, x_i))}{\sum_{i=1}^n \exp(-D(x, x_i))} \quad (1)$$

where y_i represents the measured target log values, n represents total number of training samples, y is the new log value while $D(x, x_i)$ is expressed as:

$$D(x, x_i) = \sum_{j=1}^p \left(\frac{x_i - x_{ij}}{\sigma_j} \right)^2 \quad (2)$$

The term $D(x, x_i)$ denotes the separation between each training point (x_i) and the input seismic attribute (x), and the total number of seismic attributes is (p). The smoothing factor (σ_j) differs in every attribute. Cross-validation is used to discover the optimal set of smoothing parameters, leaving out some of the training

data in the process (Hampson *et al.*, 2001) and thereafter, the conjugate gradient method is then used to minimize the validation error (Todorov, 2000).

4.0 Data and Methods

A seismic full-stack prestack depth migration volume with a record duration of 5 s and sampled at 4 ms is available for this study. Again, deterministic inverted volumes and geostatistical inverted P-impedance volumes already inverted in a previous study were used in this present study. The interpretation data included two picked seismic horizons that represent top of reservoirs F and H. The survey area was pierced through by five wells, which were all vertical. The well logs were provided in ASCII digital format. Due to proprietary considerations, the renamed wells were Well 25, Well 26, Well 27, Well 30 and Well 48. The logs include resistivity log (RT in Ohm-m), gamma ray log (GR in API unit), density log

(DEN in g/cm³) and sonic log (DT in μ s/ft). In addition, water saturation (Sw) logs were calculated from empirical relations.

Many machine learning algorithms have demonstrated their validity and significant accuracy in predicting various reservoir properties. One of these algorithms is the PNN, which was developed by Hampson *et al.* (2001) and Mohamed *et al.* (2014). The PNN can be used for classification or prediction of reservoir properties. In the prediction mode, the algorithm trains a neural network to predict reservoir properties away from the well control using information from multiple wells and seismic data. The procedure used in this study consists of three major steps: determining the best set of attributes using the multi-linear regression technique, network training, and validation. Figure 2 is a flowchart that summarizes the PNN steps. Sw was predicted using Hampson-Russell software by the PNN procedure employed.

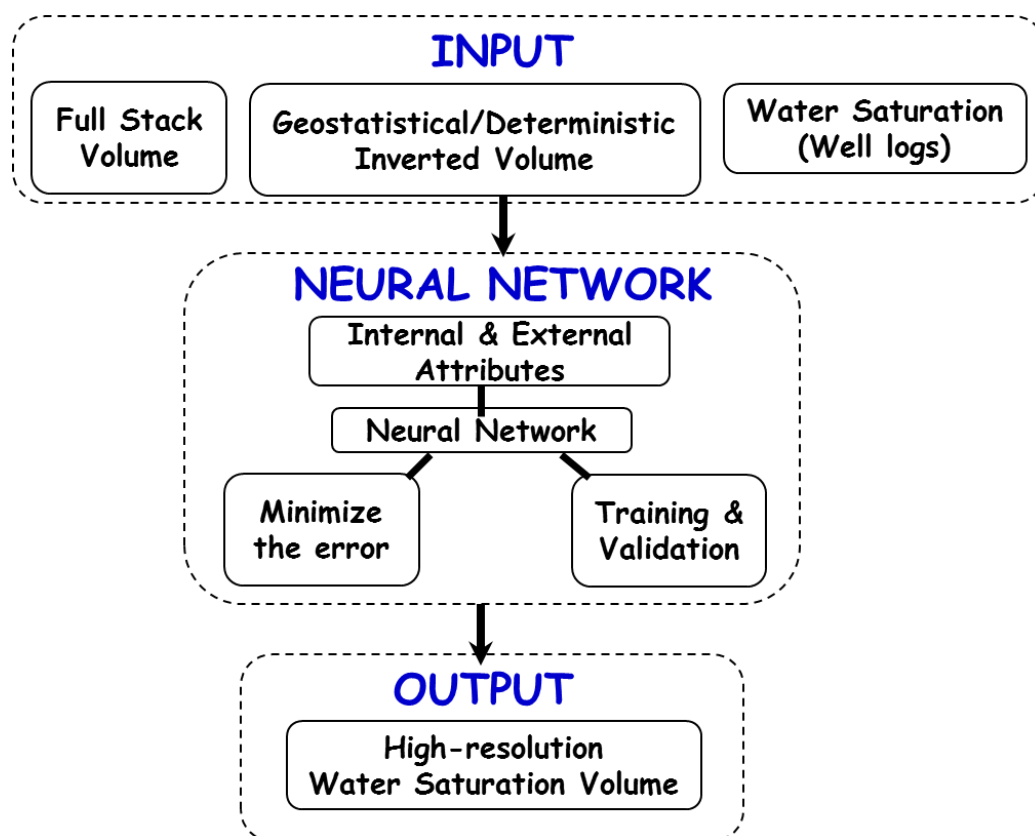


Figure 2: Flowchart showing a summary of PNN steps.

First, the logs were filtered, re-sampled, and smoothed in order to match the vertical scale of seismic data. This was done using a median filter characterised by an operator length of 5 in the Hampson Russell's eLOG tool. The network was then trained using conditioned well-log data as well as seismic internal and external attributes. Simultaneously, the network was validated by concealing some of the wells and predicted using the trained network to match the vertical scale of the seismic data. We can determine the best number of attributes and operator length for each log using the validation error plot shown in Figure 3. When a ten-point operator is used with ten attributes, the smallest validation error occurs. Any other combination leads to a greater validation error. The order and number of attributes used to train and

validate the PNN, as well as the training and validation errors are shown in Table 1. The input attributes for Sw prediction were: Dominant frequency, frequency filter 15/20-25/30, apparent polarity, frequency filter 35/40-45/50, instantaneous phase, frequency filter 45/50-55/60, frequency filter 45/50-55/60, frequency filter 25/30-35/40, frequency filter 55/60-65/70 as well as amplitude weighted phase. The probabilistic neural network was trained and validated using these attributes. In the prediction of Sw logs, the PNN performs well. The correlation coefficient with actual logs was 0.904. Following network training and validation, the trained neural networks were applied to the seismic data volume to generate 3D Sw volumes.

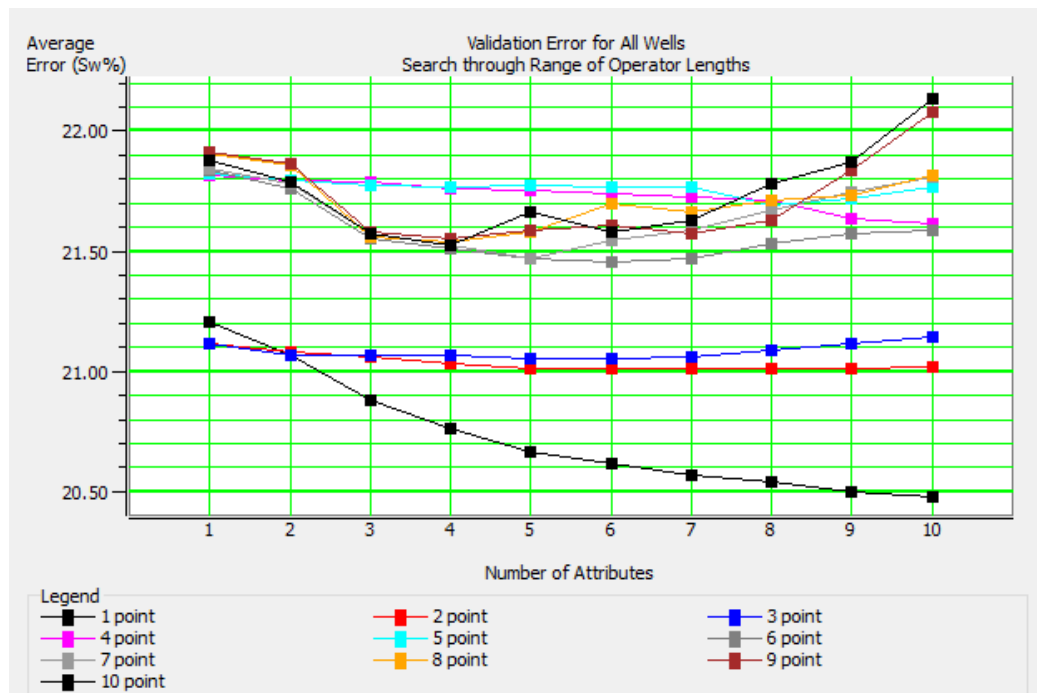


Figure 3: Validation error plot for different operator lengths. The minimum validation error occurs when a ten-point operator (black curve) is used with ten attributes. A list of the attributes is given in Table 1.

5.0 Results and Discussion

In the current study, PNN estimation was used to determine the petrophysical parameter (water saturation) away from wellbore that can resolve non-linear interactions. The non-linear relation between well-log attributes and seismic features

can be established using a neural network technique. Using external pre-stack inverted elastic attributes (acoustic impedance) as well as sample-based internal seismic (instantaneous, windowed frequency, filters, derivatives, integrated, and time) attributes, this

relationship is used to calculate the well-log property at every location throughout the seismic data. The success of the method can be measured quantitatively by calculating the mismatch between the predicted and original S_w logs. The accuracy of the results can be evaluated by calculating the correlation

between the predicted and original logs. The correlation between the predicted and actual S_w logs was 90.42% average correlation coefficient, with a 9.60% error, as shown by crossplots for the three wells considered (figure 4).

Table 1: List of order and number of attributes that are used to train and validate the PNN. The training and validation errors are shown in the right two columns

Attribute	Training error	Validation error
Dominate Frequency	20.740	21.888
Apparent Polarity	20.644	21.795
Frequency Filter 15/20–25/30	20.268	21.580
Instantaneous Phase	20.216	21.530
Frequency Filter 35/40–45/50	20.093	21.668
Frequency Filter 45/50–55/60	20.074	21.590
Frequency Filter 45/50–55/60	20.031	21.635
Frequency Filter 25/30–35/40	19.980	21.789
Frequency Filter 55/60–65/70	19.975	21.880
Amplitude Weighted Phase	19.952	22.141

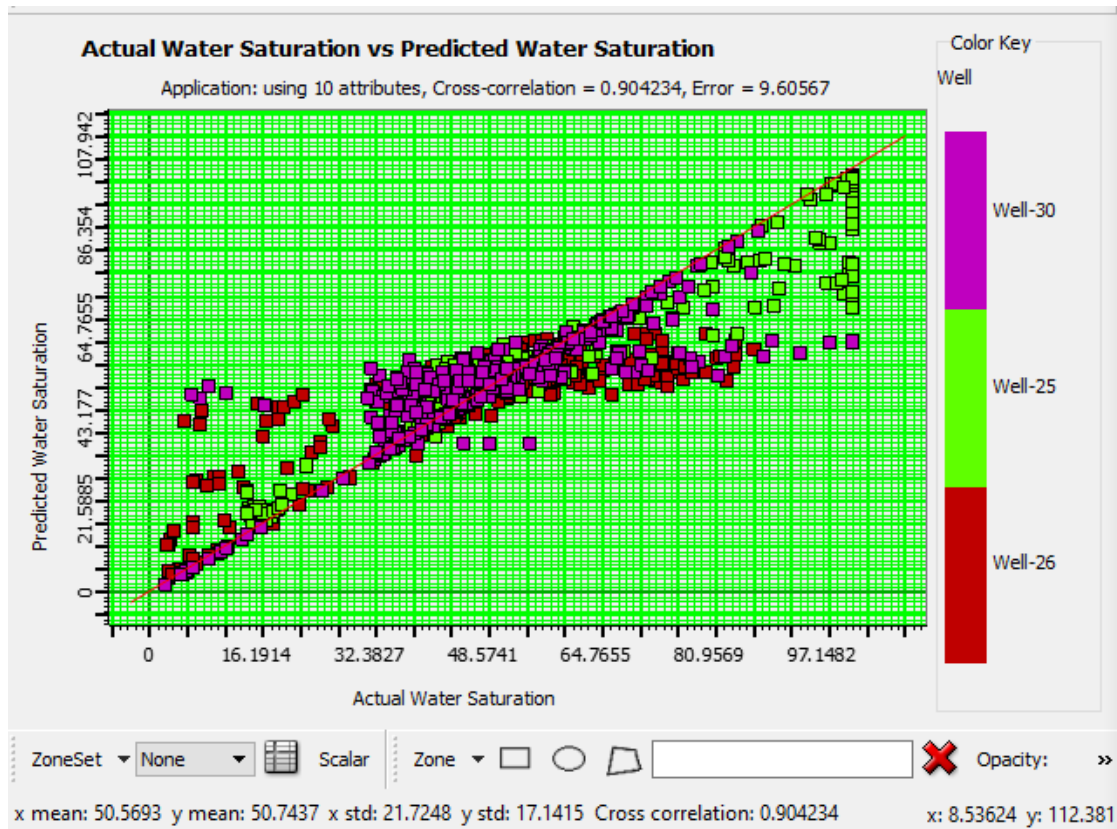


Figure 4: Original Water Saturation logs (x-axis) versus Predicted Water Saturation values (y-axis) for each well, showing 90% average correlation coefficient.

The PNN methods produced high-resolution Sw volumes for both reservoirs Sand F and Sand H. Figure 5 depicts the prediction of PNN based on deterministic inversion. The smoothed, or more averaged, water saturation result from the deterministic inversion result is shown by the PNN prediction. As seen in figure 5, the values of water saturation vary around the Sand F and H reservoirs mostly between 17% and 58%. The PNN prediction from geo-statistical inversion, shown in Figure 6, retains more of the high-frequency content as shown by the water-saturation logs. Figures 7a and 7b compare the Sand F of deterministic and high-resolution geo-statistical inversions for water saturation. Figures 8a and 8b, respectively, compare Sand H for water saturation using high-resolution and deterministic geo-statistical inversions. In figure 7a, regions around the well locations, especially around the well 26 and 30

locations have average water saturation values ranging between 4% and 17%. Table 2 displays the average water saturation values from three wells in the Sand F and Sand H reservoirs. The percentages range from 33 to 41%, with an average of 36%. The water saturation estimations from wells are consistent with the seismic predictions made by PNN in the reservoir regions, validating the method's effectiveness. The PNN model's high predictability can be attributed to its ability to respect reservoir heterogeneity and accurately predict reservoir properties. Given that the accuracy of the PNN prediction is dependent on many factors, including the quality of the well-log and seismic-amplitude data, any imaging artefacts or poor illumination zones are likely to result in incorrect reservoir property predictions.

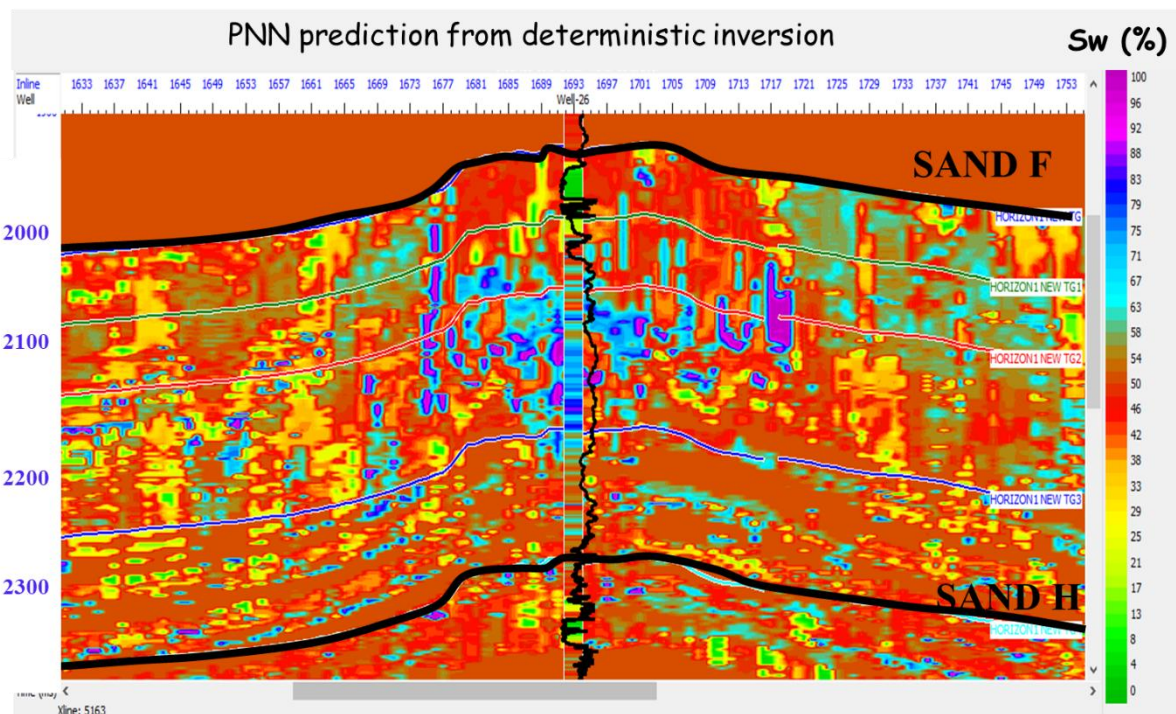


Figure 5: Water-saturation predictions using PNN prediction from the deterministic inversion

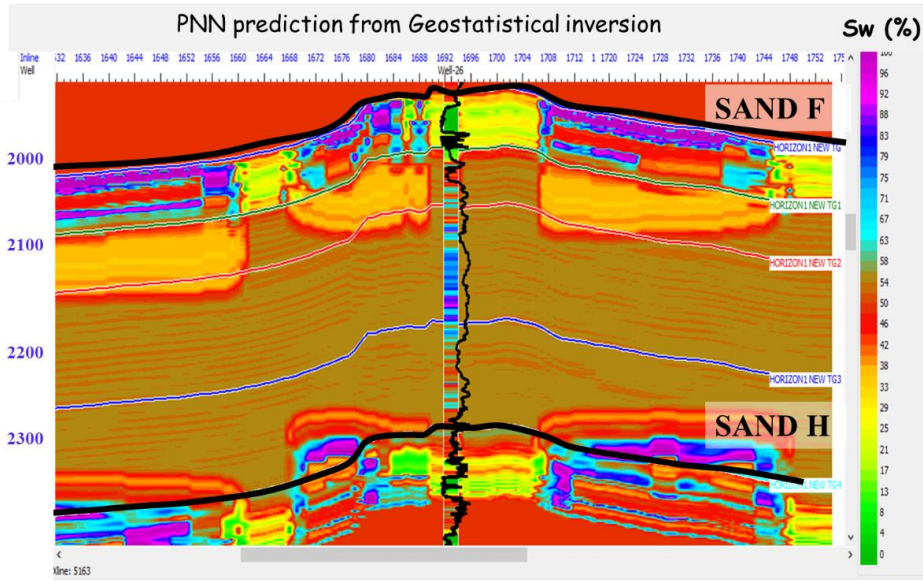


Figure 6: Water-saturation predictions using PNN prediction from the geostatistical inversion

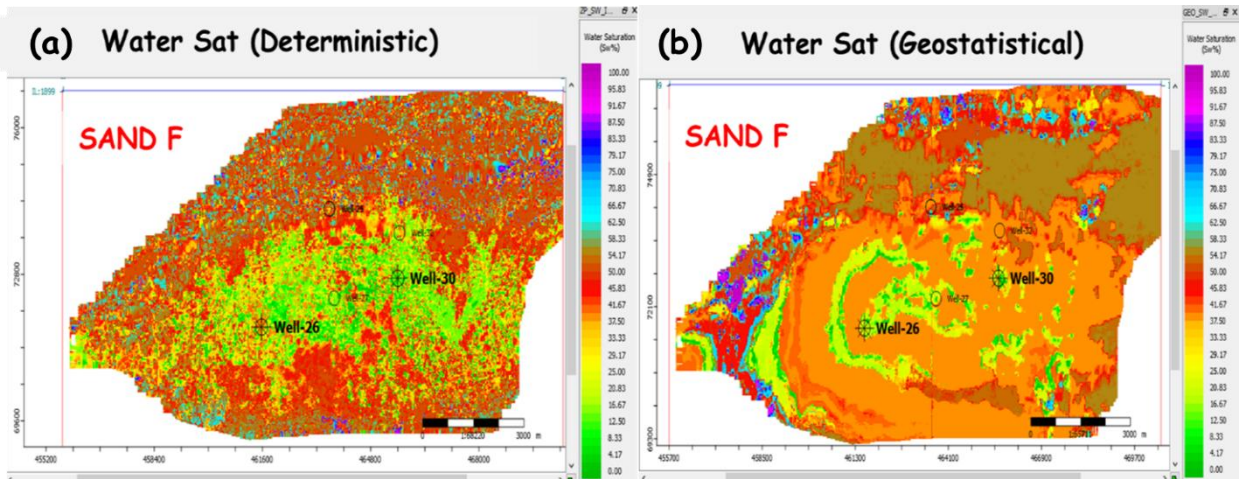


Figure 7: Comparison of horizon of deterministic (a) and high-resolution geostatistical inversion (b) for water saturation from Neural Network

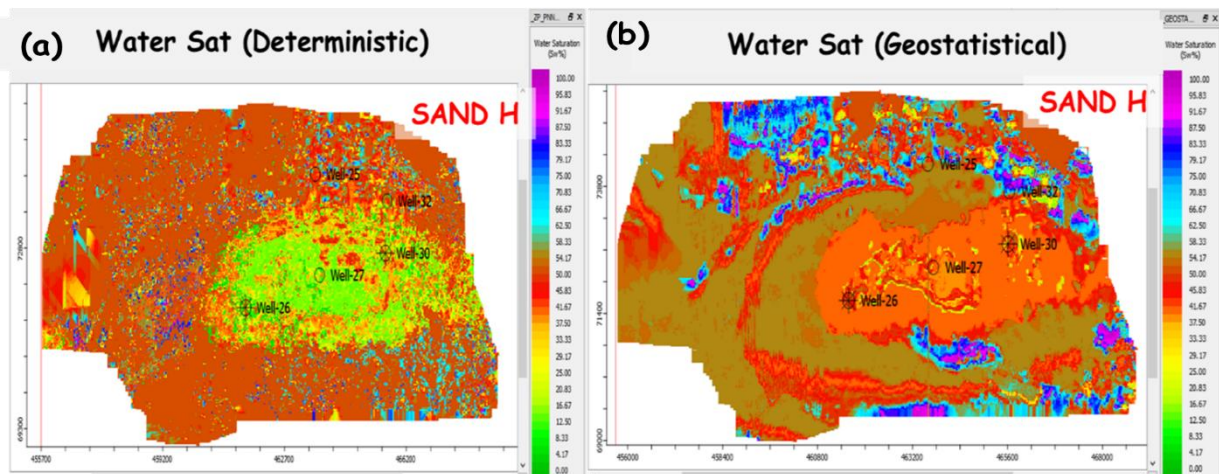


Figure 8: Comparison of horizon of deterministic (a) and high-resolution geostatistical inversion (b) for water saturation from Neural Network

Table 2: Average Petrophysical properties for three wells in reservoir Sand F and Sand H

Sand F				
Well Name	Top	Base	Sw (Frac)	S _h (Frac)
Well-25	9791	9964	0.385	0.615
Well-26	10413	10745	0.326	0.674
Well-30	10443	10752	0.375	0.625
Sand H				
Well Name	Top	Base	Sw (Frac)	S _h (Frac)
Well-25	10262	10435.94	0.408	0.592
Well-26	11039	11209.48	0.334	0.666
Well-30	11113	11178.6	0.343	0.657

6.0 Concluding Remarks

To characterize heterogeneous reservoirs, a quantitative geophysical approach was used to estimate water saturation in 3D seismic data and well logs from a field in Nigeria's Coastal Swamp Depobelt. The workflow is straightforward and consists of three steps. The first step is to load and validate input seismic data and Sw logs, calculate seismic internal attributes and condition Sw logs. The second step is to train the network with the conditioned well-log data and seismic internal/external attributes, then validate it by hiding some wells and predicting them with the trained network. The trained network was then applied to the seismic data in the third step. The probabilistic neural network method successfully predicted water-saturation 3D volume, which is an important factor in seismic reservoir characterization. Water saturation ranges from 33% to 50%, which corresponds to well log averages.

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