CLASSIFICATION OF RESERVOIR SAND-FACIES DISTRIBUTION USING MULTI-ATTRIBUTE PROBABILISTIC NEURAL NETWORK TRANSFORM IN "BIGOLA" FIELD, NIGER DELTA, NIGERIA

Alao O. A.* and Oludare T. E.
Department of Geology, Obafemi Awolowo University, Ile-Ife, Nigeria
* Corresponding author's Email Address: olade77@yahoo.com
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ABSTRACT

This study estimated reservoir properties, classified the reservoir sand-facies distribution and identified potential hydrocarbon pay zones. This was with a view to optimizing placements of wells in "Bigola" Field. Conventional interpretation of seismic and well datasets was carried out to provide the sub-surface structures and general stratigraphy of the study area. The 3-D seismic data volume along with well logs were analysed using multi-attribute Probabilistic Neural Network (PNN) transform to generate target reservoir properties (V_{shale}, Porosity and Resistivity) and consequently horizon based maps. The generated structure maps of target horizons TMTS4 and TMTS5 showed closures at the north central and north eastern parts. The generated reservoir property maps showed the distribution of reservoir sand-facies in the wells and inter-well regions. Average porosity values ranged from 22-30%, V_{Shale} values ranged between 8 and 12 % and resistivity values ranged between 112 and 199ohm-m for hydrocarbon reservoir sands. The study concluded that the reservoir sand-facies of the north eastern and north central parts of the study area were more indicative of hydrocarbon presence than those of other parts.

Keywords: Porosity, Resistivity, V_{shale}, Multi-Attribute, Neural Networks, Well and Niger Delta.

INTRODUCTION

The area of study is located in the "Bigola" Field of the offshore western Niger Delta area of Nigeria.The Niger Delta Basin which is situated along the Gulf of Guinea, has been a scene of intense study in the recent past because of its economic potential as a petroliferous province. Several oil and gas fields have been discovered within this basin and at present, more exploration works have been shifting from the onshore region to the deeper offshore portion of the basin. Hydrocarbon accumulation resides within the unconsolidated to semi – consolidated sands of the Agbada Formation where they occur within both structural and stratigraphic traps.

Sand reservoirs can either be hydrocarbon-bearing or water-bearing. Reservoir sand-facies mapping is efficient in identifying exploration prospects and predicting reservoir quality in both stratigraphic and structural prospects by recognizing genetically related volumes of strata deposited during discrete intervals of geologic time.

Reservoir sand-facies classification on 3D seismic data set involves interpreting seismic data to characterize the heterogeneity of the reservoirs facies. Sand-facies are interpreted by inspecting the data in various regions of the reservoir and grouping them together based on the characteristics of the seismic response in these regions. This grouping, or classification, is performed either visually by examining the raw trace itself or attributes derived from the trace, with the help of graphical aids like cross-plots and star diagrams, or by automatic techniques. Matlock *et al.* (1985), used a Bayesian linear decision function to identify the boundaries of rapidly varying sand facies; Simaan (1991), developed a knowledge-based expert system to segment the seismic section based on its texture; and Yang and Huang (1991) used a back-propagation neural network for detecting anomalous facies in the data.

In this study, Multi-Attribute Probabilistic Neural Network Transformis applied to 3D seismic and well log datasets from 'Bigola' Field, Niger Delta, through post stack inversion transform to demonstrate relevant reservoir properties such as acoustic impedance, porosity, resistivity and water saturation, for the well and inter-well regions in a plan view projection.

Post stack inversion transforms a single seismic data volume into acoustic impedance through integration of seismic data; well logs and a basic stratigraphic interpretation (i.e. formation tops and interpreted horizons). The resultant acoustic impedance volume can be used to predict target reservoir properties away from well locations and thus are able to better map the extent of the reservoir sand-facies and to give a qualitative estimate of reservoir sand-facies quality. Sand-facies classification correctly locates pay and non-pay facies allowing for prediction of oil saturation and reservoir connectivity, including porosity and barrier baffle locations (Carmen *et al.*, 2015).

Srivastava *et al.* (2013), analyzed a number of reservoir properties (Porosity, Resistivity and Vshale) and optimize the restricting conditions for each of the property in order to delineate and separate the hydrocarbon bearing sands from those of the water bearing sands and shales.

The analysis, however suggests that these three reservoir properties taken together may be employed to corroborate the objective to define the hydrocarbon bearing reservoir sands and their aerial distribution over the study area.

This study is thus aimed at providing a robust estimate of reservoir properties, for classification of reservoir sand-facies distribution and consequently identifying potential hydrocarbon pay zones for well placement optimization in the study area.

LOCATION AND GEOLOGY OF THE STUDY AREA

"Bigola" Field is located offshore, Western Niger Delta, between latitudes 4° N and 6° N and longitudes 3° E and 9° E (Figure 1).

The Niger Delta is located in the southern part of Nigeria, bounded by the Gulf of Guinea and in the North by older Cretaceous elements such as the Anambra Basin, Abakaliki Uplift and Afipko Syncline. The lithostratigraphic sequence of the Niger Delta are; Akata Formation, Agbada Formation and Benin Formation (Avbobvo, 1978; Doust and Omatola, 1990). The two structural styles in the Niger Delta are growth faults and rollover anticlines(Figure 2). Throughout the geologic history of the delta, its structure and stratigraphy have been controlled by the interplay between rates of sediment supply and subsidence. Important influences on sedimentation rates have been eustatic sea-level changes and climatic variations in the hinterland. Subsidence has been controlled largely by initial basement morphology and differential sediment loading of unstable shale (Doust and Omatsola, 1990).

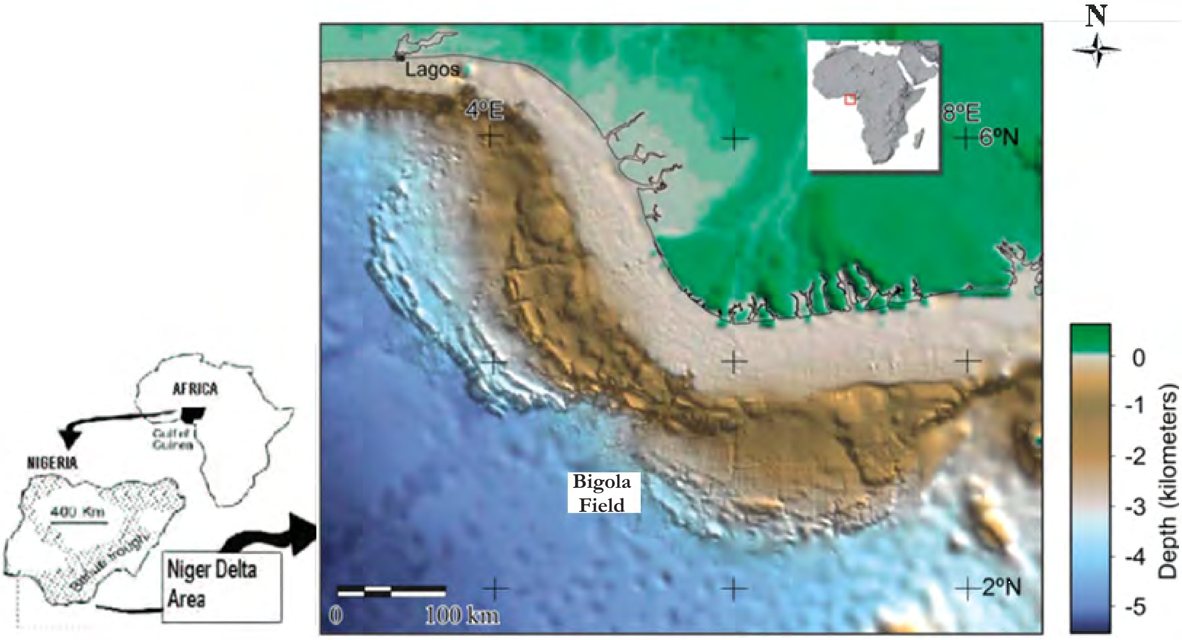

Figure 1: Bathymetric Sea-Floor Image of the Niger Delta Obtained from a Dense Grid of Two-Dimensional Seismic Reflection Profiles and the Global Bathymetric Database Showing the Location of the Study Area (Smith and Sandwell, 1997, as cited in Corredor *et al.*, 2005).

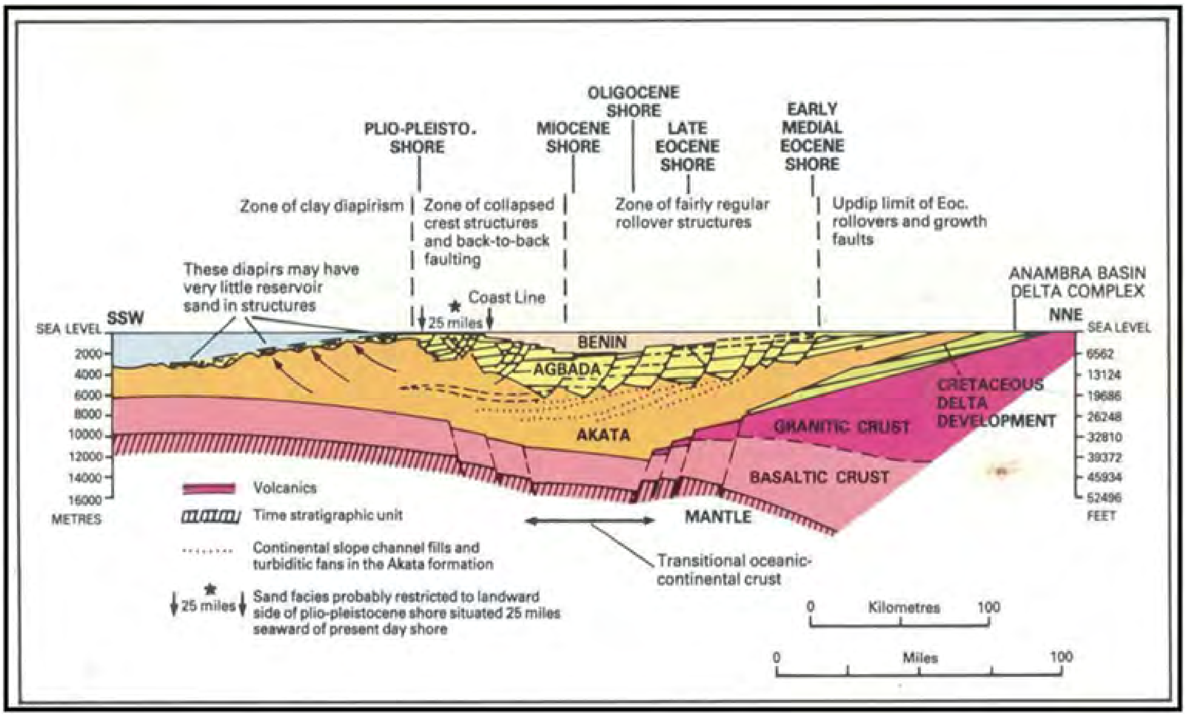

Figure 2: A Generalized Dip Section of the Niger Delta Detailing the Subsurface Formations and the Structural Styles (Adapted from Whiteman,1982).

MATERIALS AND METHOD

The materials used for this study were obtained from the Department of Petroleum Resources (DPR), Nigeria. These materials include a processed 3-D seismic volume, a suite of well logs and check shot data from six wells. The in-lines and the cross-lines range in numbers from 5800 to 6200 and 1480 to 1700 respectively, covering a total area of 71.33 km^2 with line spacing of 2.5 km (Figure 3). The borehole logs from the six wells which are coded TMB 001, TMB 002, TMB 003, TMB 004, TMB 005 and TMB 006 respectively include gamma ray, density, neutron, sonic and a number of resistivity logs. These logs and the 3D seismic data set were loaded into RokDoc, Petrel and Hampson Russell software for conventional interpretation. The 3D Seismic data were tied to the well log data with a generated synthetic seismogram.

Well Log Interpretation, Fault Picking and Horizon Mapping

Gamma ray and Resistivity logs were interpreted to identify hydrocarbon reservoir sands by studying their log signatures. Cross plotting of well log data (Resistivity - Gamma Ray cross plots and V_{shale} - Acoustic Impedance cross plot)was done using RokDoc software to eliminate the uncertainty generated by the overlap of impedance value range of the hydrocarbon sands with those of water bearing sands and shales and to optimize the restricting conditions for each of the reservoir properties in order to isolate the hydrocarbon bearing sands from those of the water bearing sands and shales (Srivastava *et al.,* 2013).

Conventional interpretation of seismic data was carried out to pick faults based on abrupt termination of events, change in pattern of events and dip of events. Horizon mapping was carried out to mark off identified reservoir formation tops from welllogs on the 3D seismic data volume aftera synthetic seismogram was generated to tie seismic to wells. The horizons were first mapped on the inlines and checked for consistency on the crosslines intercepting them.

Post Stack Inversion Analysis

A statistical wavelet was extracted and used to carry out well to seismic correlation. Subsequently an initial model was built using sonic log, density log and interpreted horizons by interpolation over the entire 3-D volume. A low pass filter (10 – 15 Hz) was applied in order to prevent high frequency components in the well data from interfering with the inversion result. Before running inversion on the 3-D volume, inversion analysis was done to

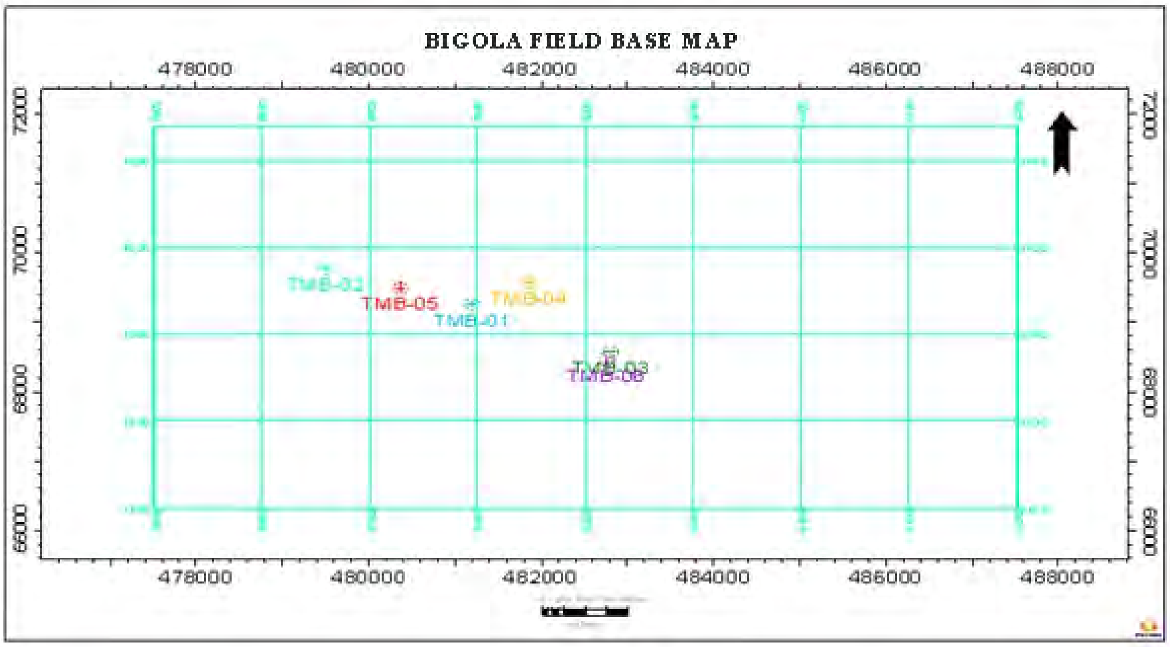

Figure 3: Seismic Base Map of the Study Area showing the Location of the Six Wells.

compare different parameters mainly with the predicted and original impedance curves. The original impedance curves were computed by multiplying sonic-derived velocity and density.

Multi-Attribute Probabilistic Neural Network

The inverted acoustic impedance volume was imported to the EMERGE platform of Hampson-Russel Software along with well logs, interpreted horizons and 3-D seismic volume for multi-attribute transform. Multi-attribute linear regression analysis was carried out to establish a linear relationship between each of the selected logs (V_{shale}, porosity and resistivity) and seismic data, using the inverted acoustic impedance volume derived by a model based post stack inversion as the external attribute. Probabilistic Neural Network (PNN) was trained to generate non-linear relationship between target logs (V_{shale}, porosity and resistivity) and the seismic-derived attributes at well locations. The trained PNN results were applied to the entire 3-D seismic data volume to compute target reservoir properties (V_{shale}, porosity and resistivity) of the subsurface and subsequently horizon based Root Mean Square (RMS) average maps of V_{shale}, porosity and resistivity of target horizons were generated.

RESULTS AND DISCUSSION

Figure 4 shows the correlation of the available wells, establishing five reservoir sands (Sand 1 to Sand 5) and their lateral continuities by picking formation tops; TMTS1, TMTS2, TMTS3, TMTS4and TMTS5 within the Agbada Formation which is the hydrocarbon window of the Niger Delta Basin.

Figures 5a and b present the results of Gamma Ray - Resistivity cross plots depicting the hydrocarbon bearing sands, fresh water bearing sand units, the shale zones and the saline water zones. The hydrocarbon bearing sand interval clusters are shown as the low acoustic impedance zone on the V_{shale} - Acoustic Impedance cross plot (Figure 5c).

The general criteria of high resistivity, low V_{shale} and high porosity values for hydrocarbon bearing sands was then adopted. The Formation tops established from the wells were used to map five horizons (TMST1, TMST2, TMST3, TMST4 and TMST5) on the 3-D seismic volume (Figure 6).

Table 1 shows the average depth, thicknesses and corresponding average resistivity values for the identified sands in the study area from well log data. Sand 4 and Sand 5 were classified as the most viable reservoir sands due to their thicknesses which ranged from 53 to 123 ft (16 to 38 m), their depths of occurrence which ranged from 10476 to 11232 ft (3194 to 3423 m) and associated high resistivity values. Though the average thicknesses of Sands 2 and 3 are greater than that of Sand 4, their corresponding low resistivity values depict them as non-hydrocarbon bearing sands and thus not viable. TMST4 and TMST5 associated with Sands 4 and 5 respectively were thus selected as target horizons for Multi-attribute Probabilistic Neural Network Analysis.

Structure Maps

The structure maps of the two most viable horizons (Horizon TMST4 and Horizon TMST5) are presented in Figures 7 and 8 respectively. Closures were identified on the structure maps generated over Horizon TMST4 (Figure 7). These closures occurred at the north central and north eastern parts of the study area which show proven and probable reserves respectively. Horizon TMST5 showed similar structures (Figure 8). These anticlinal closures were identified as good traps and are therefore possible hydrocarbon prospects.

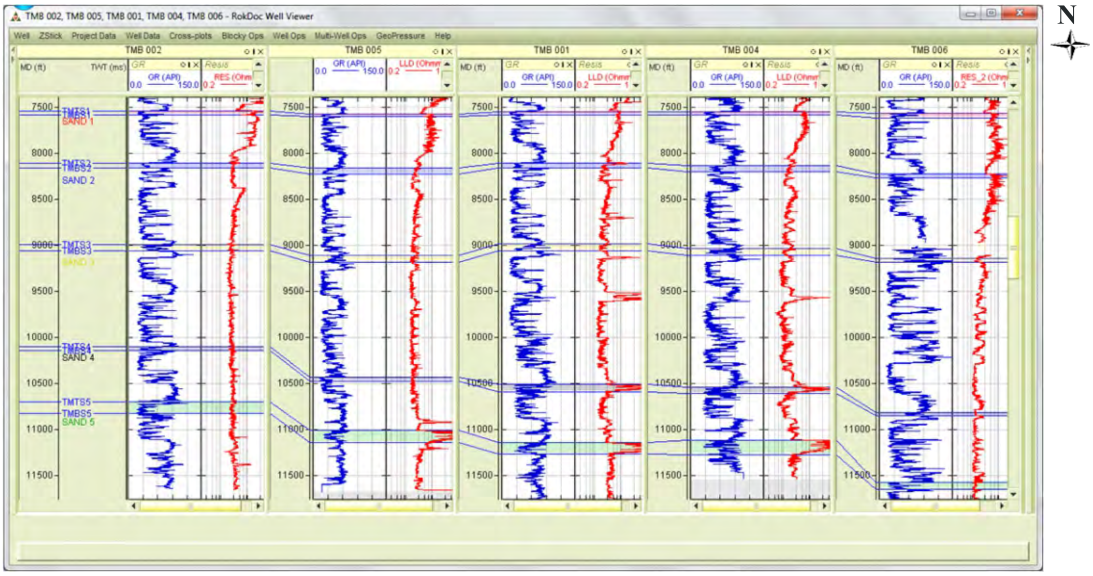

Figure 4: Well Correlation of the Identified Reservoir Sands and their Lateral Continuity (Produced with RokDoc Software, Version 6.1.4)

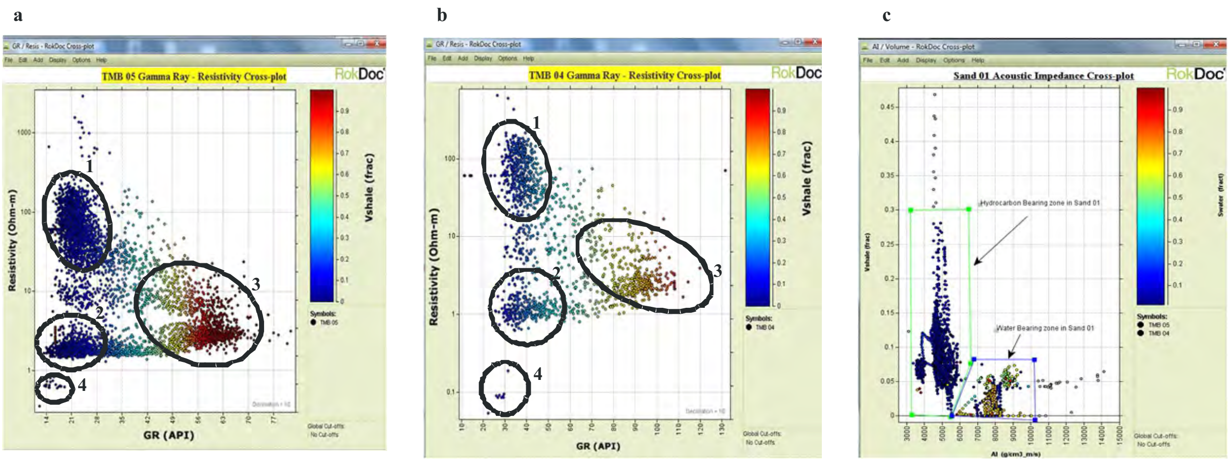

Figure 5: Cross Plot Analysis of Well Logs in the Study Area. **(a)** and **(b)** Depict the hydrocarbon bearing sand units **(1)** as zones of high resistivity, low gamma ray and low V_{shale}, the fresh water bearing sand units **(2)** as zones of low resistivity, low gamma ray and low V_{shale}, the shale **(3)**, as zones of low resistivity, high gamma ray and high V_{shale}, and the saline water zones **(4)** as clusters of very low resistivity, very low gamma ray and low V_{shale}. **(c)** Depicts the hydrocarbon bearing sand interval cluster as the low acoustic impedance zone (Produced with RokDoc Software, Version 6.1.4).

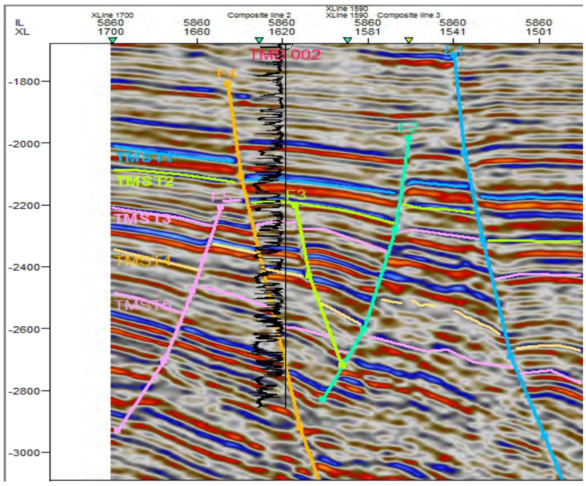

Figure 6: Seismic Section of Inline 5860 Showing the Fault Segments and Interpreted Horizons (Produced with Petrel Software, 2010).

Table 1: Depth and Average Thicknesses of Identified Sand Units

	Average Start Depth		**Average End Depth**		**Average Thickness**		**Average Resistivity**
	ft	**m**	**ft**	**m**	**ft**	**m**	**(Ω-m)**
Sand 1	7554.13	2302.50	7585.58	2312.08	31.44	9.58	90
Sand 2	8146.05	2482.92	8203.47	2500.42	57.41	17.50	40
Sand 3	9051.02	2758.75	9118.00	2779.17	66.98	20.42	76
Sand 4	10476.56	3194.17	10532.96	3210.45	53.31	16.25	124
Sand 5	11108.38	3385.83	11231.41	3423.33	123.03	37.50	177

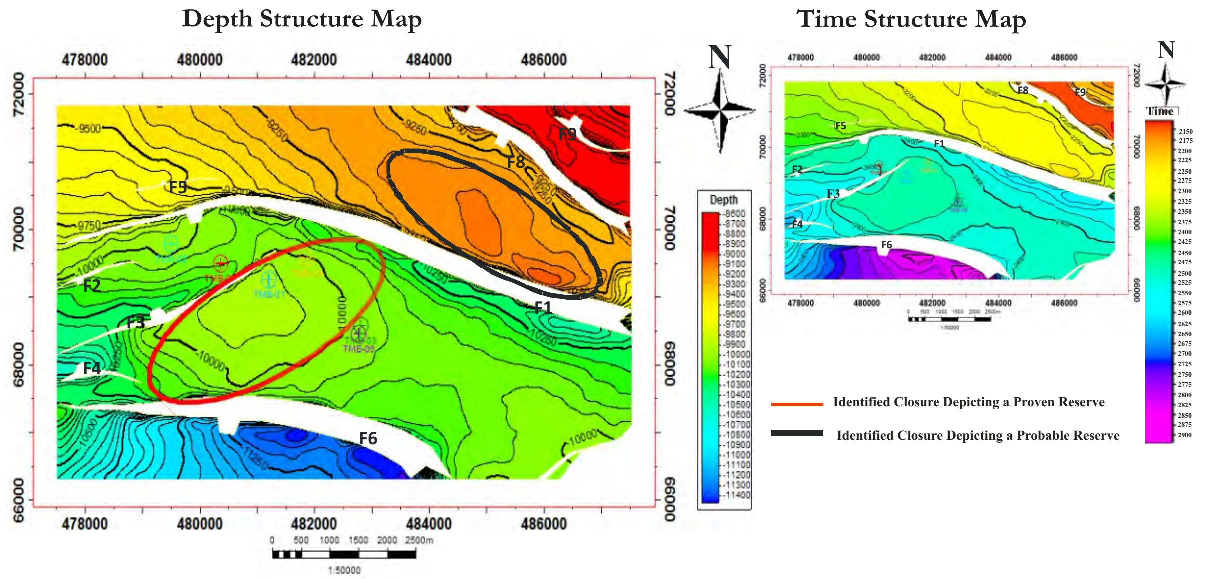

Figure 7: Depth and Time Structure Maps of Horizon TMST4 Showing Identified Fault Polygons and Closures(Produced with Petrel Software, 2010).

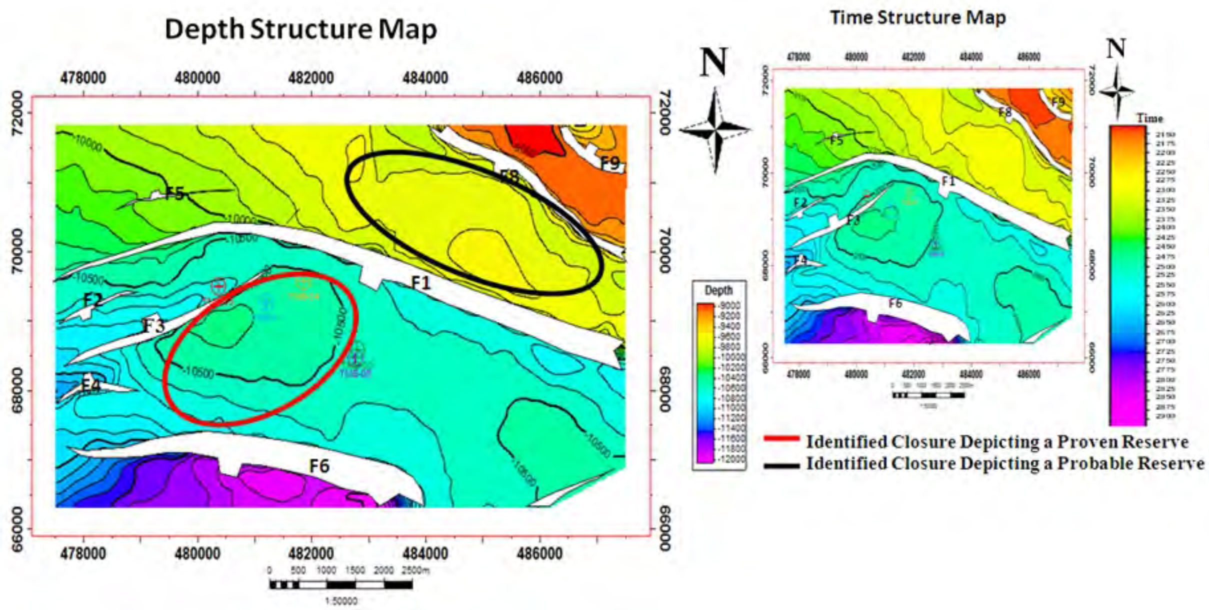

Figure 8: Depth and Time Structure Maps of Horizon TMST5 Showing Identified Fault Polygons and Closures(Produced with Petrel Software, 2010)

Horizon Based RMS Maps of Computed V_{shale}

Horizon based RMS average computed V_{shale} maps for TMST4 (top of Sand 4) and TMST5 (top of Sand 5), within the Agbada Formation were generated (Figures 9 and 10). The sands appear cleaner where the V_{shale} value is relatively low (2 - 12 %). V_{shale} distribution for TMST4 showed high degree of shaliness (18 – 30 %) from the central part to the South eastern and South western parts but cleaner sands at the North eastern and North western parts (Figure 9). However, the V_{shale} distribution of TMST5 offers clean sand which appear promising with V_{shale} values ranging from 5 – 16 %, from the central part to the North eastern, North western and South western parts of the study area (Figure 10). The computed V_{shale} map shows the overall V_{shale} distribution and also shows that the non-hydrocarbon bearing wells (TMB 003 and TMB 006) penetrated shaly sands at the target horizons TMST4 and TMST5 in the study area(Figures 9 and 10).

Horizon Based RMS Average Map of Computed Porosity

Horizon based RMS average computed Porosity maps for TMST4 and TMST5 were generated (Figures 11 and 12). Porosity values ranged from 20 to 28 % for the hydrocarbon bearing sands in the study area. Both computed porosity horizon maps for TMST4 and TMST5 show sand facies development at the North central part of the study area. The same sand facies extends to the North eastern and South western parts. Correlating the computed V_{shale} ranging between 2 and 22% with the computed porosity(20 – 28 %), it could be inferred that the possible hydrocarbon sands show good development towards the North central and South western parts of the study area for both the TMST4 and TMST5 sand conform with the locations of hydrocarbon bearing wells in the study area (TMB 001, TMB 004 and TMB 005).

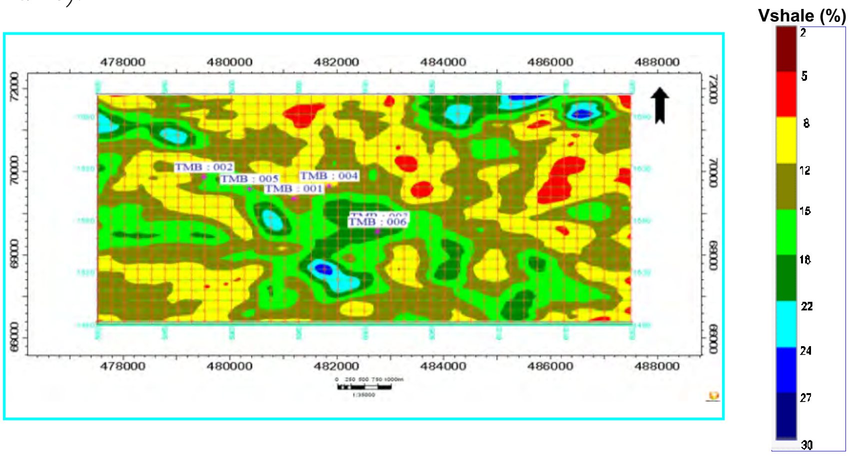

Figure 9: Horizon Based RMS V_{shale} Map of TMST4 Showing the Sand-Facies Distribution (Produced with Petrel Software, 2010).

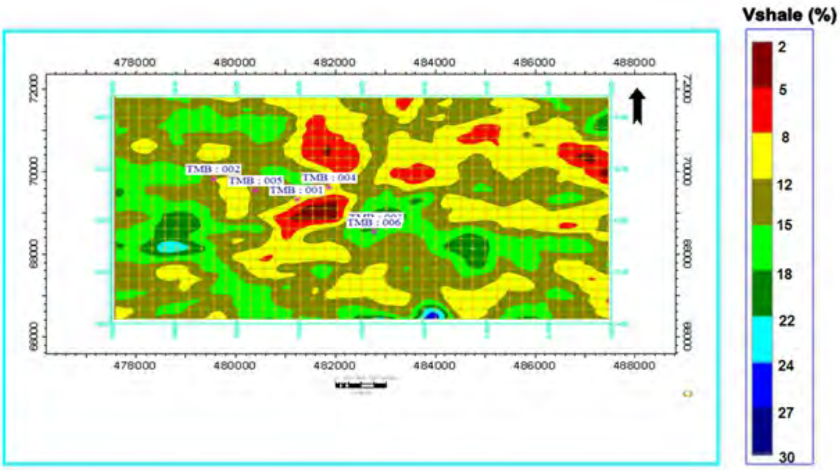

Figure 10: Horizon Based RMS V_{shale} Map of TMST5 Showing the Sand-Facies Distribution (Produced with Petrel Software, 2010).

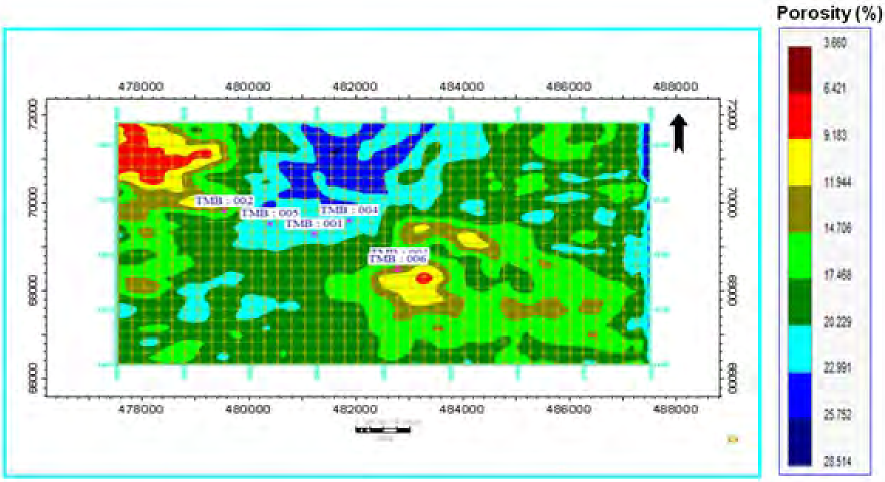

Figure 11: Horizon Based RMS Porosity Map of TMST4 Showing the Sand-Facies Distribution (Produced with Petrel Software, 2010).

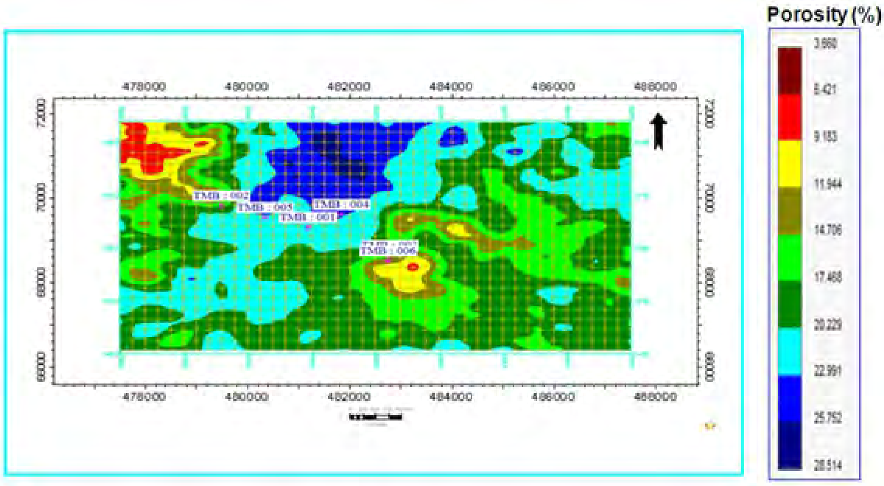

Figure 12: Horizon Based RMS Porosity Map of TMST5 Showing the Sand-Facies Distribution(Produced with Petrel Software, 2010).

Horizon Based RMS Average Map of Computed Resistivity

Horizon based RMS average computed Resistivity maps for TMST4 (Sand 4) and TMST5 (Sand 5) (Figures 13 and 14) were generated. Moderate to high resistivity values (of between 100 – 200 Ωm) were considered typical of the hydrocarbon bearing sands.

TMST4 shows moderate to high values of resistivity at the North central part. The North eastern and South eastern parts are characterized by low resistivity values ranging from 43 - 95Ωm (Figure 13) while TMST5 shows moderate to high values of resistivity at the North central, North eastern and South western parts of the study area. The North western and South eastern part are also characterized by low resistivity values (Figure 14).

Integrating the computed reservoir properties (V_{shale}, Porosity and Resisti distributions with the generated structure maps, the sands-facies in the North eastern and North central parts of the study area can be said to be highly indicative of hydrocarbon accumulation. The South western and North western parts of the study area showed partial hydrocarbon accumulation (fizz water), while the South eastern part did not give encouraging results.

CONCLUSION

3D seismic volume and well logs were analyzed using multi-attribute Probabilistic Neural Networks (PNN) to generate target reservoir property volumes (V_{shale}, Porosity and Resistivity) using Hampson-Russel software.

The comparison of the target reservoir properties was based on the general criteria that; low acoustic impedance, low V_{shale}, high Porosity and high Resistivity typify hydrocarbon-bearing sand-facies. Based on the result obtained, the hydrocarbon bearing sand-facies were identified with low V_{shale} (<12 %), high Porosity (20 - 28 %) and high Resistivity (>110 Ωm).

The comparison of the generated reservoir property maps (V_{shale}, Porosity and Resistivity) and the generated structure maps of target horizons showed that the sands in the North western and North central parts of the study area were more indicative of hydrocarbon accumulation. Both the South western and North eastern parts of the study area showed partial hydrocarbon accumulation, while the South eastern part did not offer encouraging results for hydrocarbon accumulation. The maps also showed that the hydrocarbon bearing wells (TMB 001, TMB 004 and TMB 005) fall within zones that are indicative of hydrocarbon accumulation.

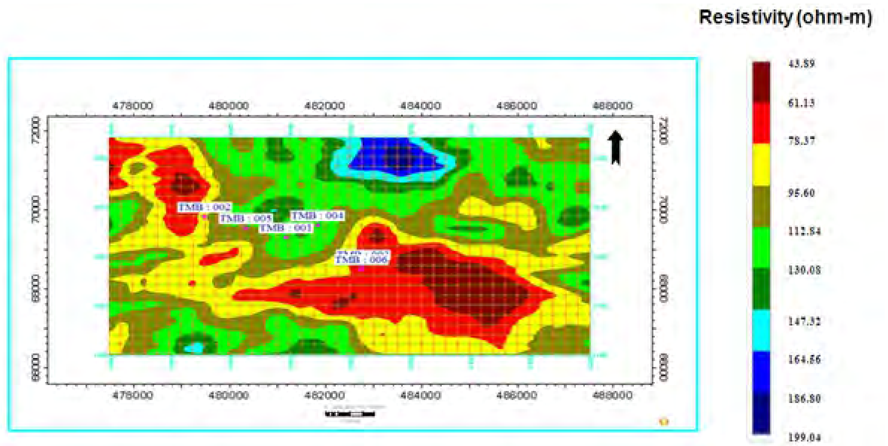

Figure 13: Horizon Based RMS Resistivity Map of TMST4 Showing the Sand-Facies Distribution(Produced with Petrel Software, 2010).

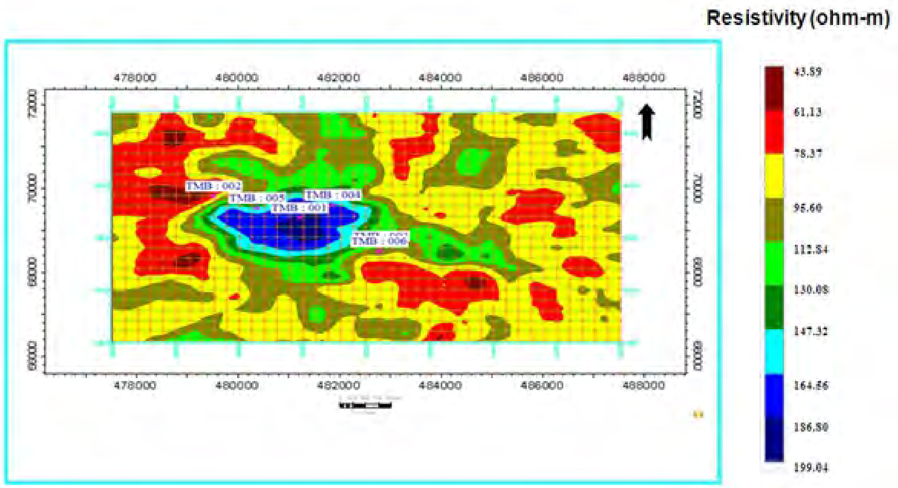

Figure 14: Horizon Based RMS Resistivity Map of TMST5 Showing the Sand-Facies Distribution(Produced with Petrel Software, 2010).

The analyses of these maps show the lateral extent of the identified reservoir sands and have given room for identification of new prospect. This could enhance the confidence level for designing optimal developmental programs for reservoir exploitation and management in "Bigola" Field.

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