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RESEARCH ARTICLE

Hydrocarbon Prospectivity in the undrilled area of AIMA Field in the Niger Delta Basin, Nigeria.

Ogbamikhumi Alexander[1,*], Ighodalo John Elvis[2]
[1] Department of Geology, faculty of Physical Sciences, University of Benin, Nigeria
[2]Department of Physics, faculty of Physical Sciences, University of Benin, Nigeria

* Corresponding author : alexander.ogbamikhumi@uniben.edu
Tel.: +2348032722203
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Abstract

Field development is a very costly endeavor that requires drilling several wells in an attempt to understanding potential prospects. To help reduce the associated cost, this study integrates well and seismic based rock physics analysis with artificial neural network to evaluation identified prospects in the field.

Results of structural and amplitude maps of three major reservoir levels revealed structural highs typical of roll over anticlines with amplitude expression that conforms to structure at the exploited zone where production is currently ongoing. Across the bounding fault to the prospective zones, only the D_2 reservoir possessed the desired amplitude expression, typical of hydrocarbon presence. To validate the observed amplitude expression at the prospective zone, well and seismic based rock physics analyses were performed. Results from the analysis presented Poisson ratio, Lambda-Rho and Lambda/Mu-Rho ratio as good fluid indicator while Mu-Rho was the preferred lithology indicator.

These rock physics attributes were employed to validate the observed prospective direct hydrocarbon indicator expressions on seismic. Reservoir properties maps generated for porosity and water saturation prediction using Probability Neural Network gave values of 20-30% and 25-35% for water saturation and porosity respectively, indicating the presence of good quality hydrocarbon bearing reservoir at the prospective zone.

Keywords: Rock Physics, Neural Network, Reservoir Properties, Cross-plot Analysis, Seismic Inversion.

1. Introduction

Seismic data play a significant role in rock physics and quantitative interpretation studies, by not only providing a structural framework of fault, fracture and geologic horizons but also helps in deducing the lateral distribution of reservoir properties (Chatterjee et al., 2016). (Ogbamikhumi et al., 2018), defined the inversion of seismic data as a tool to derive rock properties (P-impedance, S-impedance, etc.) from seismic, that is linkable to reservoir properties (Porosity, lithology, pore fluids, etc.) using rock physics models and statistical techniques. The inversion process involves inverting the simplified Zoeppritz equation (Zoeppritz, 1919) to generate earth reflectivities, which are in turn incorporated to estimate rock attributes for lithology and fluid discrimination during reservoir characterization (Edwards and Santogrossi, 1990) (Stacher., 1995). (Castagna and Swan, 1997), (Toshev, 2017), (Goodway., 2001), (Adeoti et al., 2018), (Abdel-Fattah et al., 2020) These inversion results are very essential data source that can be integrated with artificial neural network to analyze and evaluate identified prospects.

In recent times, geoscientists have employed methods of Artificial Intelligence, particularly Neural Networks (NNs), to predict several reservoir properties from well logs and seismic for field (Leite et al., 2011), (Adojoh et al., 2017). An integration of quantitative seismic interpretation techniques with artificial neural network were adopted in this study to identify and evaluate a prospect in an under appraised field with limited well penetrations.

The Study field is situated within Niger Delta Basin, and the basin is located in the Gulf of Guinea (Figure 1). Based on the initial work by (Short et al., 1967), well Penetration in the center of the Basin reveals three major Lithostratigraphic formational units. The rock units include the under-compacted shales of the Akata Formation, the Paralic sand and shale units of the Agbada formation and the continental fluvial sands of the Benin Formation (Edwards and Santogrossi, 1990). Majority of the exploited reserve are trapped within the sands of the Agada Formation. The Basin is structurally complex and is divided into sub basins referred to as Depo-Belts. It is characterized by listic faults with simple rollover anticlines and collapse crest structures and antithetic faults, typical of some of its trapping mechanism. (deltas and 1995, n.d.)

2. Materials and Methods

An integrated technique that includes Rock Physics cross plot analysis, model base inversion, and Probability Neural Network were adopted to evaluate the reservoir of interest at the exploited zone of the field. Well based rock Physics cross-plot analysis were carried out to identify suitable rock attributes and template for lithology and fluid discrimination on seismic (Goodway, 2001), suggested four rock attributes (Vp/Vs ratio or Poisson ratio, Lambda-Rho, Mu-Rho and P-wave Impedance) for lithology and pore fluid discrimination, which were selected among others in this study.

The choice of model base inversion in this study is such that it provides us with several output results, which were used in the network training process, thereby improving the quality of the predicted results. Some of the major inversion results that served as input into the training process include; the Low frequency model, the generated synthetic volume, inverted P-impedance volume, Inverted P-wave volume and the Inverted Density volume.

Theories and discussion on application of neural network for field evaluation are well documented in the work of (Li, 1994). Several authors have demonstrated that feed forward networks (especially the Probability Neural Network (PNN)) are the most commonly used and reliable neural network technique for prediction and correlation of properties in geological processes (Mokhtari et al., 2011). Hence, The PNN Technique was employed in this study to predict aerial distribution of porosity and water saturation.

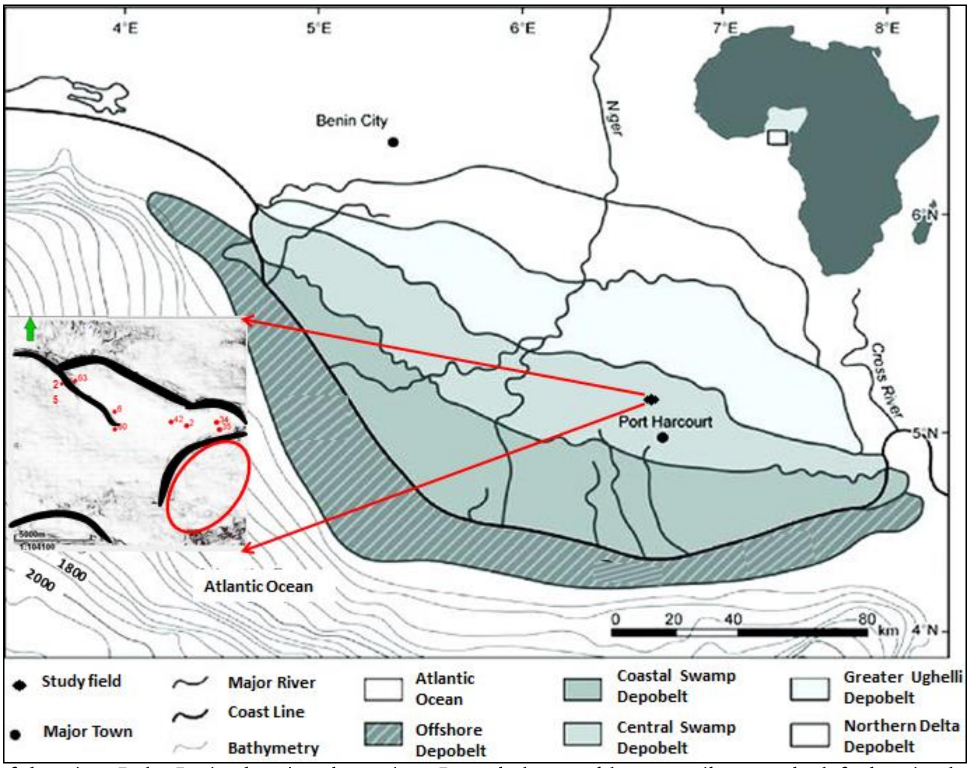

Fig. 1. Map of the Niger Delta Basin showing the various Depo-belts, semblance attribute to the left showing location of the prospective zone (Red ellipse) of the study Field, the available wells (Red number labels) and north direction (Green arrow) (Modified after (Adojoh et al., 2017)).

3. Results and Discussion

Three prominent reservoirs in the field were identified and selected from production records to evaluate their hydrocarbon potential in the prospective zone, where anticlinal traps have been observed (Figure 2). The top structure maps of the potential prospective C_3, D_2 and D_7 reservoirs reveals a structural high; a potential trap (Asquith et al., 2004) at both the exploited and prospective zone (Figure 3a, 3b and 3c). RMS (Root mean Square) amplitude was extracted from the interpreted surfaces to compare the amplitude expression of the exploited zones to the prospective zone. Analysis of the amplitude map of the reservoirs at the exploited zone reveals amplitude signature that conforms to structure at the three reservoir levels (Figure 3d, 3e and 3f), which agrees with well information.

At the prospective zone, it was observed that only the D_2 reservoir level expresses amplitude signature similar to what was confirmed as hydrocarbon bearing in the exploited zone of the reservoir (Figure 3e). Hence, the D_2 reservoir level was selected as the prospective reservoir for further evaluation at the prospective zone.

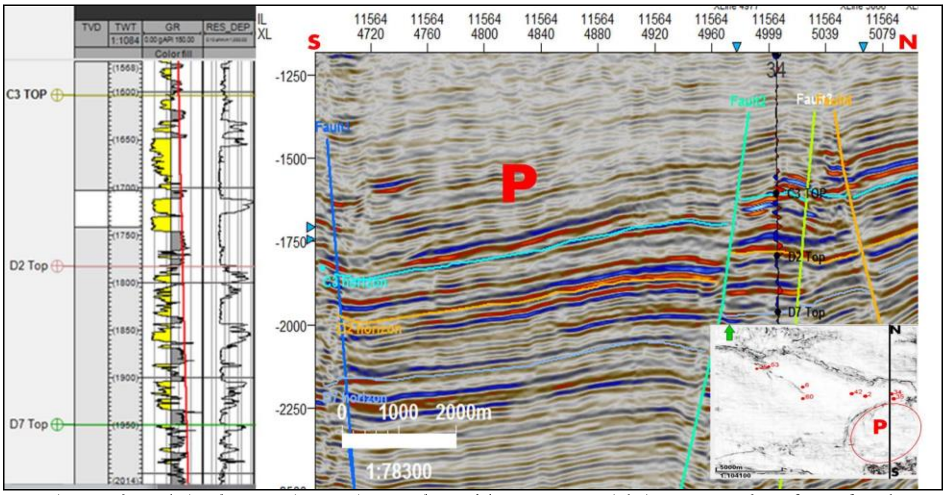

Fig 2. Prospective and exploited zones in section and semblance map with interpreted surfaces for the prospective reservoirs. (The prospective zone is marked “P” while the exploited zone is the region with well penetrations). To the left on the image is a well section window that displays the referenced well 34 indicating positions of the prospective reservoir (C3, D2 AND D7 WITH high GR response) and hydrocarbon response (High Resistivity response). Semblance to the right indicates the position of the available wells(red lables), the position of Dip line 11564 (Black line and the prospective area of the field (Marked P in the red ellipse)

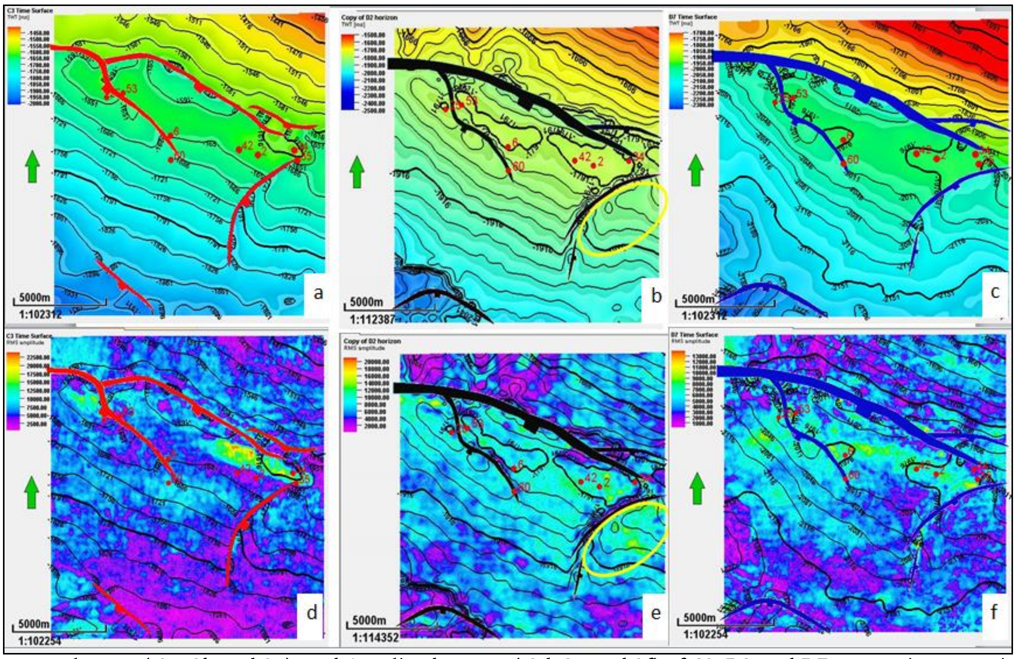

Fig 3. Structural maps (3a, 3b and 3c) and Amplitude Maps (3d, 3e and 3f) of C3, D2 and D7 reservoir respectively that reveals the presence of structural traps across the three prospective reservoirs, and response indicative of hydrocarbon presence at only the prospective region of D2 reservoir (3e).

3.1.Well Based Rock Physics Cross Plot Analysis

Well base rock attributes cross plot analysis were conducted using well data from the exploited zone of the field in order to establish their sensitivity to both lithology and fluid changes, which could help justify the application of rock physics studies from inversion to evaluate prospect on seismic (Ogbamikhumi et al., 2018). Generally, common lithology units and fluid types tend to form separate clusters in cross-plot space and this helps in making a straightforward interpretation (Omudu et al., 2005). The rock attribute cross-plot template employed for the well based cross plot analysis of the D_2 prospect includes; Mu-Rho versus Lambda-Rho, Poisson Ratio versus P-Impedance and Lambda-Rho versus Lambda-Rho/ Mu-Rho (Figures 4,5 and 6 respectively). Results of the cross-plots reveal a high value of Mu-Rho as an indicator of the possible presence of sand, and considerably low for shale presence, since shale lithology possess a low tendency to deform by shearing as seismic wave propagates across. Hence Mu-Rho is considered as is a good lithology discriminator as evidence in figure 4 (Castagna and Swan, 1997), Lambda-Rho, Poisson ratio and Lambda-Rho/ Mu-Rho have been presented as a good fluid discriminant (Omudu et al., 2005). Very high values for these parameters indicate the presence of Shale lithology while Low values are indicator of sand presence. A much more lower values in most cases signifies the presence of hydrocarbon presence as evidence in figures 4,5 and 6. The cross plots are colour coded with resistivity logs to help validate hydrocarbon presence. As observed in these plots, very high values of resistivity coincides with very low values of the fluid indicators, this is due to the less-conductive behaviour of the reservoirs when brine are being replaced with hydrocarbon, as compared to the lower values for the very conductive shale lithology. The crossplot analysis has demonstrated that these rock attributes can be adopted to conveniently evaluate the undrill areas of the prospective reservoir on seismic by analyzing similar rock parameters derived from seismic inversion.

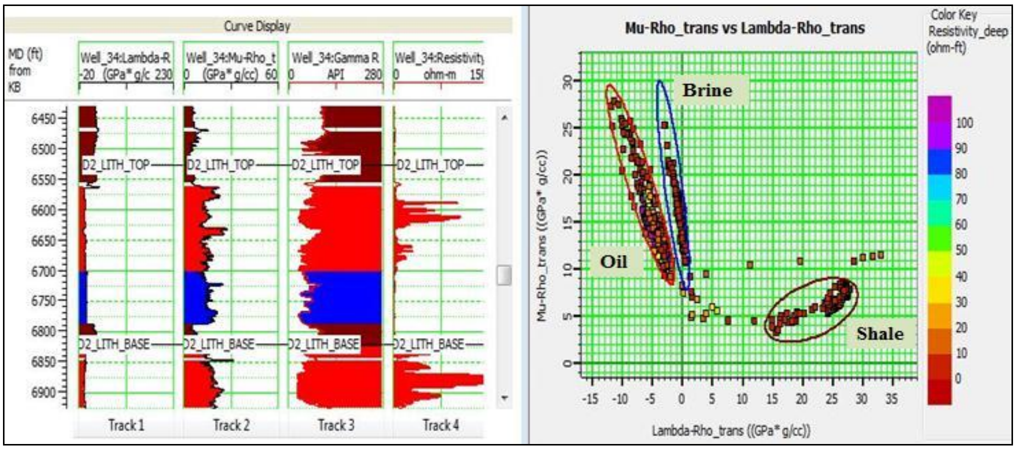

Fig 4. **W**ell sections showing the plotted attributes and intervals (To the left) and cross Plot of Mu-Rho versus Lambda-Rho for lithology and fluid discrimination (To the right).

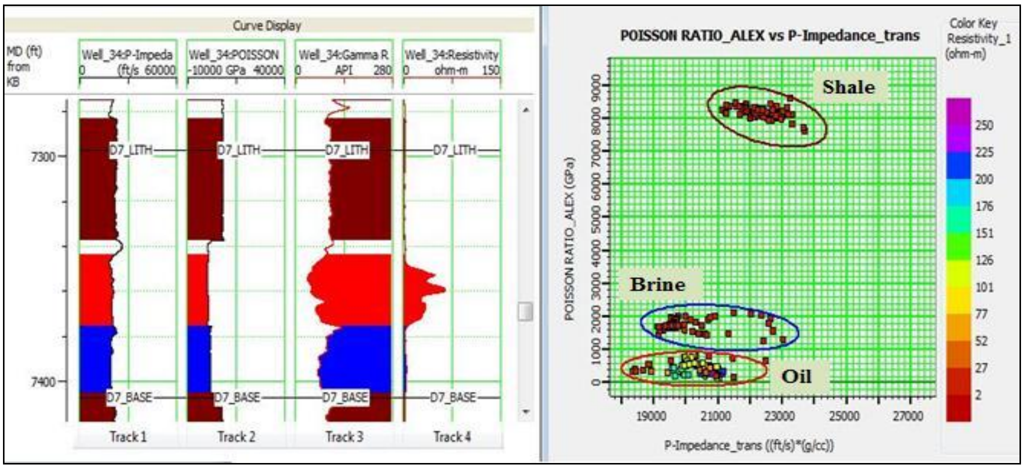

Fig 5. **W**ell sections showing the plotted attributes and intervals (To the left) and a cross plot Poisson Ratio versus P-Impedance for lithology and fluid discrimination (To the right of figure).

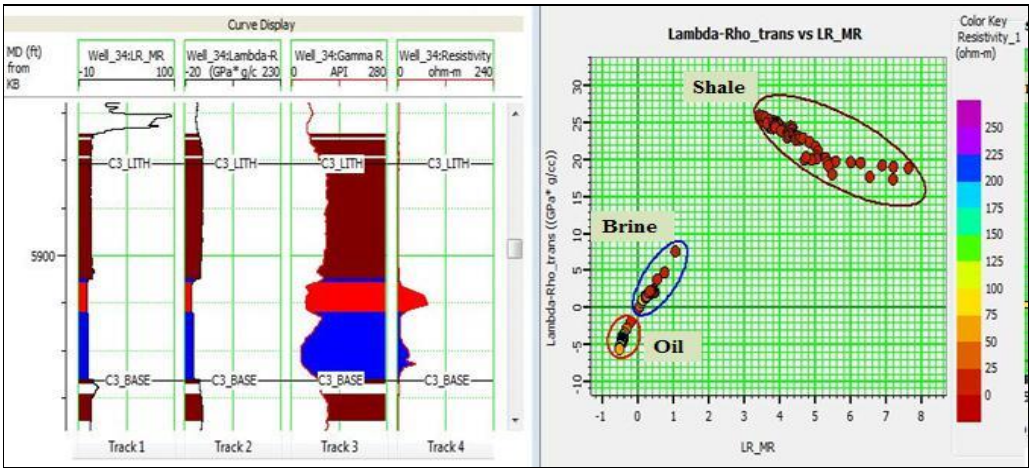

Fig 6. **W**ell sections showing the plotted attributes and intervals (To the left) and a cross plot Lambda-Rho versus Lambda-Rho/ Mu-Rho for lithology and fluid discrimination (To the right of figure).

3.2 Seismic Based Rock Physics Analysis for D2 prospect

Validation

Analysis of the seismic inversion process is presented in figure 7. The correlation between correlation of inverted synthetic logs and well derived synthetic logs shows a very good result with correlation coefficient between 0.83 to 0.94, as such, the inversion result is very good and dependable for subsequent interpretations from seismic. The error associated with inverted P-impedance logs were observed to be on the high side for well 61 and 1; hence they were excluded from the final inversion process subsequent neural network reservoir properties prediction process.

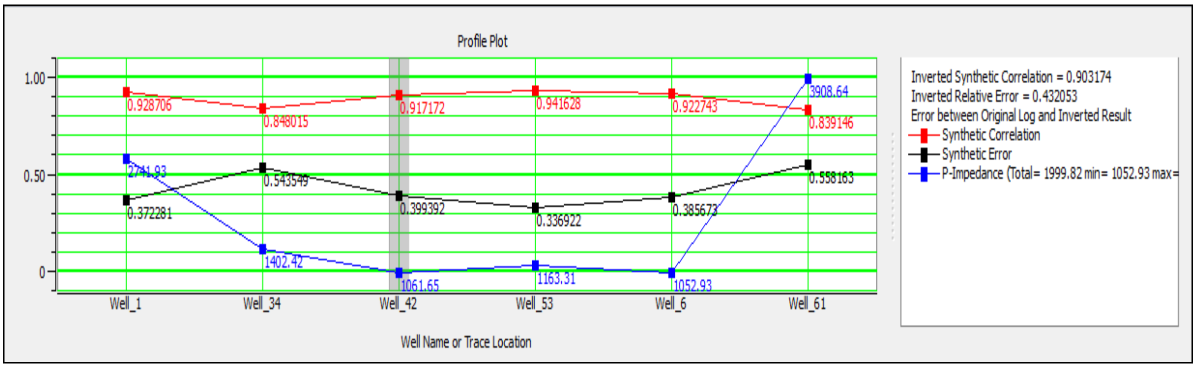

Fig 7. Synthetic correlation, relative error and P-impedance error for the six wells available for inversion for the selection of the appropriate wells with less errors.

Maps of these selected parameters were generated from inversion the inversion results for seismic based rock analysis to evaluation the identified D_2 prospect. Mu-Rho attribute's map was generated to determine the presence of reservoir response in the prospective zone (Figure 8a). As observed from the legend, the prospective zone have very high Mu-Rho value between 13.0-16.2 Gpa, expected for reservoir response, similar to the response at the exploited zone where hydrocarbon sands have been produced, confirming the presence of good quality sand .

From the well based cross plot, sands are expected to have low Lambda-Rho values. For hydrocarbon bearing sands, the values are expected to be much lower. Lambda-Rho values observed on the map ranges between -1 to 9.5 GPa. But within the prospective zone a much lower response with value between -1 to 4.3 exists in the structurally highest region indicating the presence of hydrocarbon within the sand (Figure 8b), which agrees strongly with the amplitude map earlier presented.

Poisson ratio is a good fluid indicator and has been demonstrated to be a viable tool for fluid presence indication. The map generated in figure 8c reveals a low Poisson ratio value between -1000 and 3000 indicating the presence of sand in the prospective zone. A much lower value between -1000 and 2000 was observed within this zone, indicative of the presence of hydrocarbon, similar to the hydrocarbon response at the exploited zone. The Poisson ratio appears to have defined a wider extent of the accumulation than earlier observed in the Lambda-Rho map; hence it gave a better indication of fluid presence in the study field than Lambda-Rho.

Lambda-Rho/Mu-rho ratio map presented in figure 8d reveals low values between -0.1 to 0.95, indicating the presence of reservoir sands. Within this zone a much smaller range of value was observed between -0.1 to 0.68 confirming that the reservoir is hydrocarbon bearing similar to response at the exploited zone. The hydrocarbon response of Lambda-Rho/Mu-rho ratio map was observed to define even greater hydrocarbon accumulation compare to Lambda-Rho and Poisson ratio. Hence the presented rock attributes have validated the identified prospect as hydrocarbon bearing in the prospective zone.

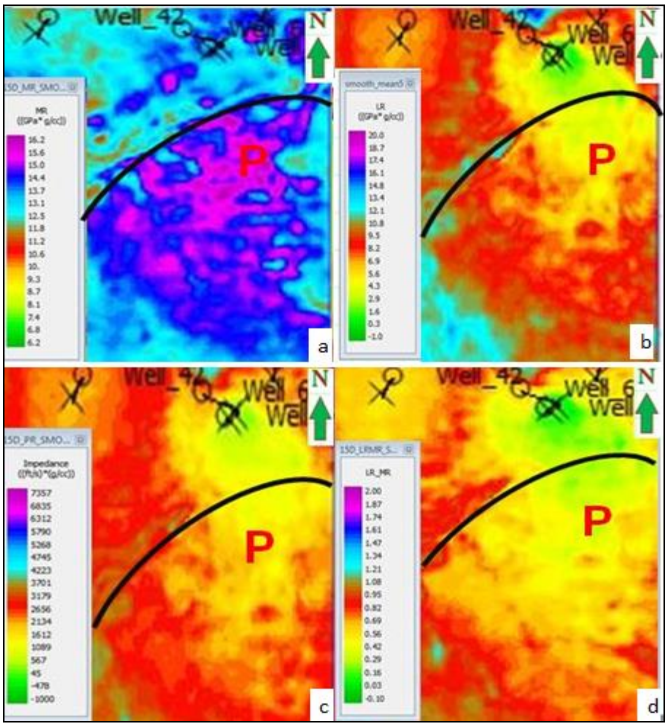

Fig 8. : Mu-Rho map of D2 reservoir confirming the presence of good quality sand (a), Lambda-Rho map of D2 reservoir showing the possible extent of hydrocarbon accumulation (b), Poisson Ratio (c) and Lambda-Rho/Mu-Rho map (d) of D2 reservoir showing the possible extent of hydrocarbon accumulation.

3.3. Reservoir properties Prediction from Neural Network

Reservoir properties were predicted from seismic derived impedance to further appraise the validated prospect. Figure 9 shows the cross plot of well derived porosity (figure 9a) and water saturation (Figure 9b) against the predicted porosity from neural network technique across the selected reservoir in the field. The correlation coefficients of both cross plots are 0.96 and 0.97 respectively, suggesting that the prediction process is of very good quality and reliable.

Reservoir properties cross section that cut through our reference well (Well 34; which is the deepest well in the field) and maps (Porosity and water saturation maps) were generated to appreciate the field wide variations (figure 10). The respective logs from our reference well and its gamma ray log were superimposed on the cross section of the respective predicted reservoir properties seismic section that cut through the well for comparism (figure 10a and 10c). It was observed that the well derive porosity and water saturation logs matches the seismic based neural network prediction result excellently especially around our time interval of interest. The prospective zone on the map reveals porosity values between 25% and 28% similar to what was observed around the exploited zone behind the fault, indicating the presence of very good reservoir (figure 10b). This zone also defined water saturation value between 20% and 30% which correspond to hydrocarbon saturation between 80% and 70%, also similar to observation around the exploited zone, confirming the presence of hydrocarbon (figure 10d).

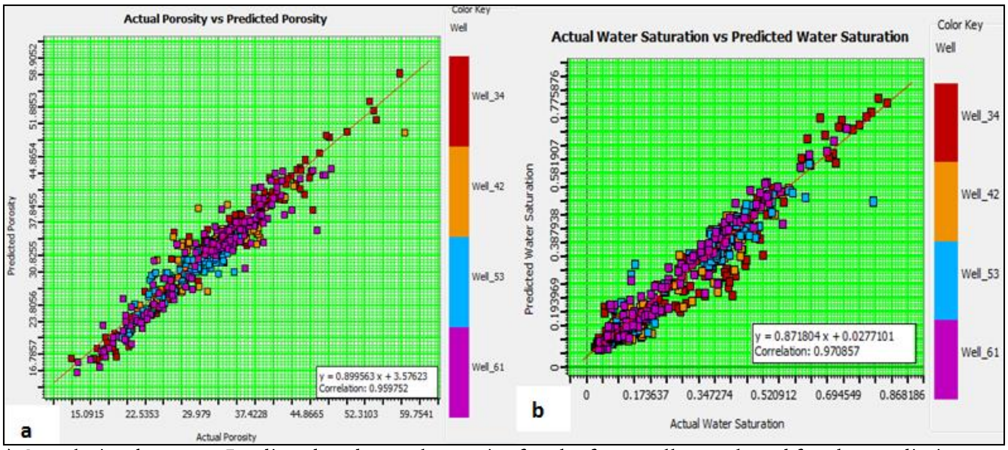

Fig 9 :(a) Correlation between Predicted and actual porosity for the four wells employed for the prediction process (b) Correlation between Predicted and water saturation with both having good correlation coefficients greater than 0.5.

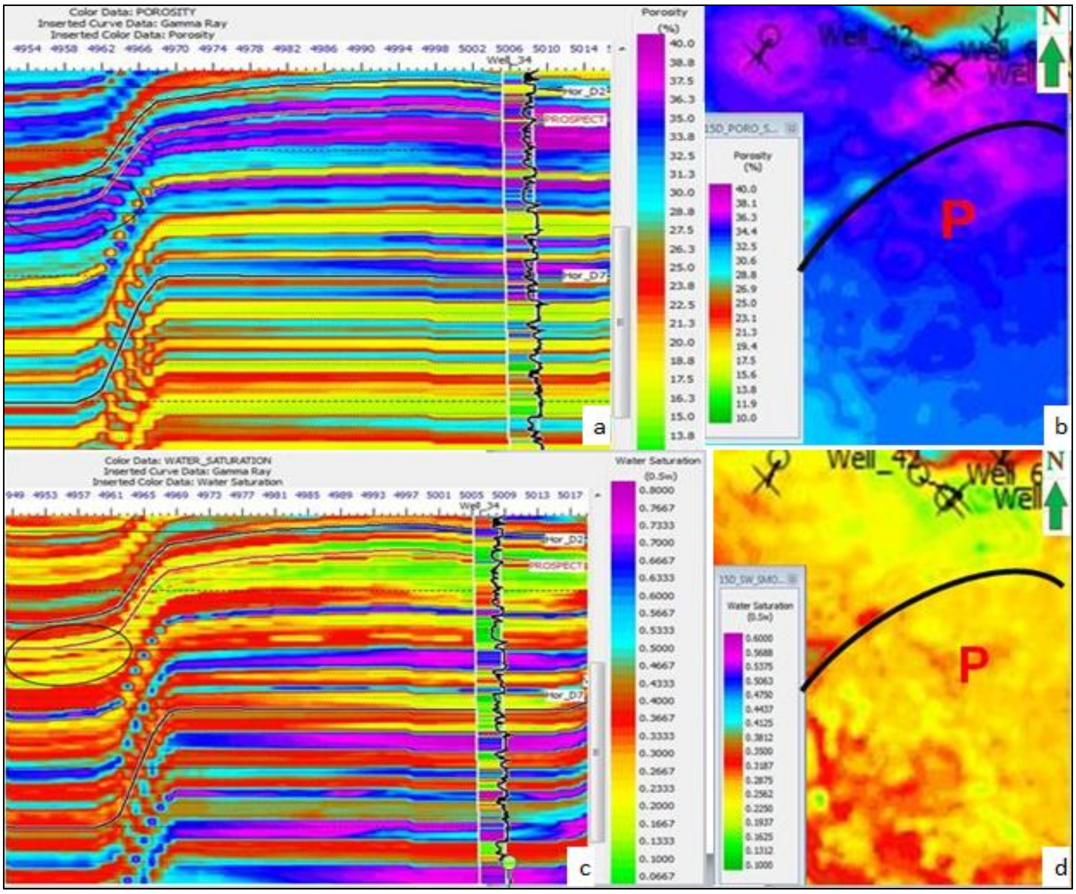

Fig 10 : Inline 11563 predicted Porosity of D2 reservoir (a), Porosity map of D2 reservoir showing the porosity distribution across the reservoir (b), Inline 11563 predicted water saturation of D2 reservoir(c), Water saturation map of D2 reservoir showing the porosity distribution across the reservoir (d)

4. Conclusion

In this research work, Rock physics and model based inversion analysis were integrated with artificial neural network for prospect identification and evaluation in the undrilled area of a field with limited well penetrations in the Niger Delta Basin. Structural and amplitude maps of the reservoirs identified response indicative of possible hydrocarbon accumulation within the undrilled area. From the well based Rock Physics cross plot analysis, Poisson ratio, Lambda-Rho and Lambda/Mu-Rho ratio were demonstrated as good fluid indicator and Mu-Rho as the preferred lithology indicator. Maps of these attributes derived from inversion result were analyzed to validate the identified prospect as hydrocarbon bearing. Reservoir properties maps for porosity and water saturation prediction using Probability Neural Network presented values between 25-28% and 20-30% respectively.

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