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Application of Rock Physics Diagnostics for Well Lithostratigraphic Correlation

Tamunonengiyeofori Dagogo 1, Ayomide Olumide Balogun *2*

1Geophysics Research Group, Department of Physics, University of Port Harcourt, Choba, Rivers State, Nigeria
nengi.dagogo@uniport.edu.ng
2Geophysics Research Group, Department of Physics, University of Port Harcourt, Choba, Rivers State, Nigeria
ayomide.balogun@uniport.edu.ng

***Abstract**: Well lithostratigraphic correlation, which is a rudimental part of the reservoir evaluation and characterization process, can generally be challenging to achieve and particularly so, in frontier exploration settings where geologic information may be limited or out rightly unavailable. To contribute to the evolution of schemes put forward to overcome this challenge and readily achieve this vital task, this endeavor explored the application of rock physics diagnostics, which enables the diagnosis of rock texture, depositional environment and diagenetic history, to the process of well correlation. This is based on the premise that; rock physics diagnostic models must be robust at identifying specific laterally continuous sedimentary units, which though may be disjointed spatially, should retain their textural and historical characteristics, and as such should aid their identification and matching across multiple wells. The technique entailed performing a fluid substitution, so as to suppress other factors that may affect the rock properties, such as fluid saturation, synthesizing elastic and reservoir properties that may not be available and cross plotting the relevant diagnostic parameters. Cross plots of compressional wave velocity (Vp) against porosity for several mapped sand zones from same and different wells, showed poor semblance between the data clusters, except for when they have similar geologic properties and history. Using this analysis, four (4) sand zones were correlated across the four wells in the field of study. The technique though subjective at the moment shows great promise for improvement and integration into emerging and evolving schemes including artificial intelligence (AI) schemes.*

Keywords: Lithostratigraphic correlation, Rock physics diagnostic, rock texture, diagenetic history.

1. Introduction

Well to well correlation, which entails matching specific lithologic units, delineated within different wells, with themselves across the wells, is a rudimental step in the reservoir characterization workflow/process, as it serves as the first phase highlighting the lateral coverage of geologic features of interest, from which a pseudo three-dimensional (3D) models of features of interest may be visualized [1] [2]. It facilitates the integration of well and seismic data and is an indispensable step essential for accurately performing seismic interpretation, reservoir characterization and constructing subsurface models. Also, it highlights early in the process, the structural disposition of a field, gives an indication of reservoir thicknesses and provides model constrain information. The process of well correlation can be onerous, particularly when dealing with formations that exhibit lithological variations laterally. Traditionally, well correlation is accomplished manually, by analyzing the form and excursions on well log data, such as gamma ray, resistivity and sonic, to highlight patterns which are indicative of stratigraphy discernible in multiple wells. This process is mostly validated by biostratigraphic data. Performing this vital process continues to be a challenge in the industry and to geoscientists, considering the time-consuming nature and particularly due to the fact the biostratigraphic information is not very readily available. In light of this challenge, several schemes have been formulated to achieve correlation, with varied levels of success. In recent times, data science and artificial intelligence schemes have been employed to enhance the process and these have had significant effect on the process and results. Powerful pattern recognition algorithms, embedded in supervised learning schemes, leveraged annotations on datasets to achieve quicker correlation, neural network schemes have also had significant improvement [3]. However, challenges may still persist, considering that these schemes are purely data node based and can be affected by structural complexity.

In this endeavor, an attempt is made to incorporate rock physics diagnostics into the process of well log correlation. Rock physics diagnostics is a rock physics analysis that highlights the stratigraphy, texture and depositional environments of reservoir units, based on their disposition and distribution on elastic moduli or velocity versus porosity cross plot space. The rock-physics diagnostics method was put forward by [4] as a means of inferring rock microstructure from velocity-porosity relations [5] [6]. The method entailed adjusting an effective-medium theoretical model curve to a trend in the data and assuming that the microstructure of the rock matches that used in the model. This technique was developed following the work of [7], which established a simple linear relationship between the velocity and porosity of water saturated sandstone [8] [9]. Following this work, other researchers, [10] [11] [12] [13] and [14], have established that sedimentary units exhibit distinct trends/distributions on the cross plot domain, when elastic moduli or velocities are cross

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plotted against porosity, based on their textures, depositional environment and diagenetic history.

Using these concepts, this work seeks to enhance the process of well lithostratigraphic correlation, in terms of reliability of results and time management. This work is carried out in a Niger Delta oil field (Figure 1). The Niger Delta is known to be one of the world's prolific oil provinces, where several large discoveries have been made, both offshore and onshore. Oil production has been on for a while such that there are several mature, brown and marginal fields in the leading, so the challenges of reservoir characterization, field development and reservoir management and monitoring are topical in the region, owing to the diverse reservoir settings found in the region, made up of five (5) main depobelts.

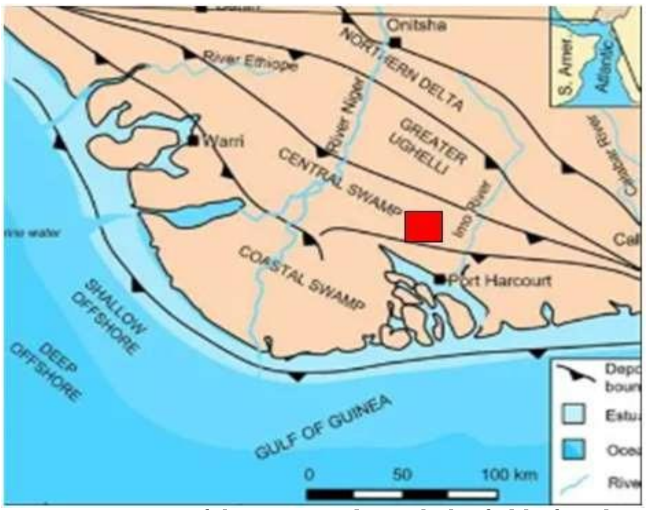

Figure 1: Map of the Niger Delta with the field of study location indicated (Red inset)

The delta is known to have three (3) stratigraphic formations, the deepest marine shales – the Akata Formation, the intermediate formation – the Agbada Formation, which typically houses the reservoirs of the delta, made basically of successions of sands and shales and the topmost formation – the Benin Formation, which is predominantly a sand formation.

2. MATERIALS AND METHODS

The materials employed for this work include well log data from four (4) wells, containing the basic logs required for petrophysical and elastic analysis, such as; gamma ray, resistivity, density, sonic and neutron porosity in a lone case, Figure 2, shows a typical well display window with available logs.

The data analysis involved delineating probable reservoir zones within each well and assigning random labels to them, synthesizing other petrophysical and elastic parameters, particularly, the bulk modulus, porosity, shear wave velocity, acoustic impedance and VpVs ratio. These were synthesized using already well established petrophysical models, having

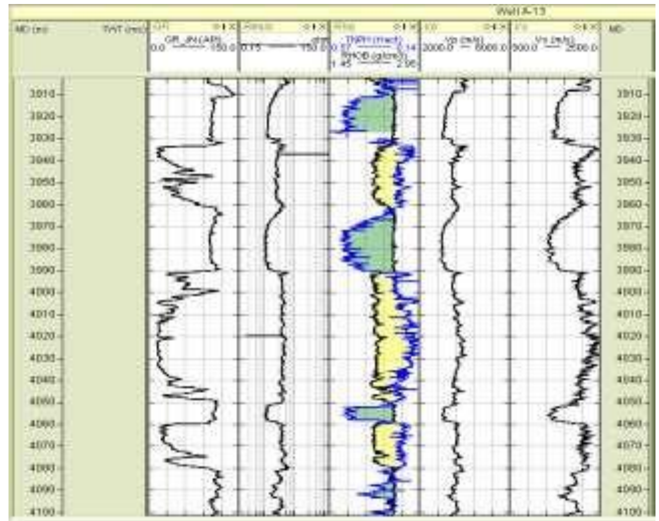
Figure 2: Typical well log window (Well A-13)

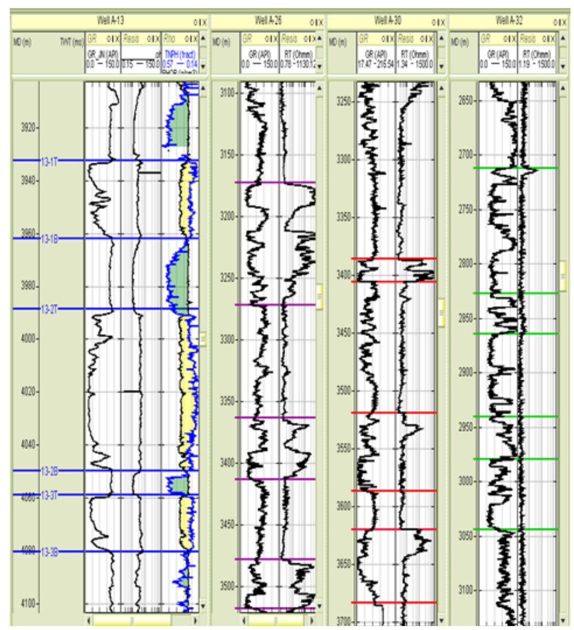
Figure 3: Wells A-13 – A32, showing mapped probable reservoir sands

performed fluid replacement modeling to back out the hydrocarbon saturation, leaving all the wells and mapped reservoirs with a common fluid denominator – brine, such that the responses observed in cross plot space, may validly be attributed to the rock properties and not any other factor. Then, cross plots of compressional wave velocity Vp and bulk modulus K against porosity were plotted for the different wells and reservoir sands, to analyze the semblance or correlation between them.

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3 RESULTS AND DISCUSSION

Rock physics models have been reported to enable the inference of the geologic properties of clastic sediments if their porosities and velocities are known, thus, in this endeavor, plots of elastic velocities against porosities of the different reservoir zones identified within different wells of the field were plotted on the same axes, to analyze their diagnostic correlation. Figure 4, shows the cross plot of Vp vs porosity for all the reservoir zones identified in the four (4) wells. This shows a scattered distribution of data points and trends, with some clustering of points across wells and sands. It gives a broad indication of the variableness of the geology of the different lithostratigraphic units mapped with some noticeable overlapping/clustering of some data points from different wells. Figure 5a-c, shows the typical cross plots of corresponding sands - in terms of depth sequence, from the four (4) wells. These plots show different trends for most of the zones, however, (a) shows some clustering between zones A30-1 and A32-1 while (b) shows correlation between A26-2 and A30-2.

More detailed and specific typical cross plots, which allow for a closer look at the data point dispositions of the sand zones, by considering just two (2) zones at a time (Figure 6a – d), shows cross plots of Vp vs Por for random zones, taken from any two (2) wells in each case. These plots show large dissimilarities between the zones plotted in each case, highlighting the difference in the geologic properties of the specific sand zones. Figure 7a-d, shows cross plots of Vp vs Por, for other zones taken from different wells, for which only, good correlation or semblance was found; (a) shows good

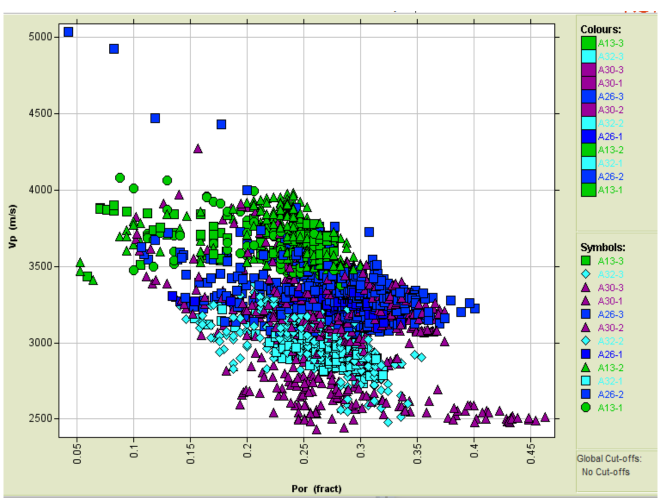

Figure 4: Vp vs Por cross plot for mapped reservoir zones in all wells

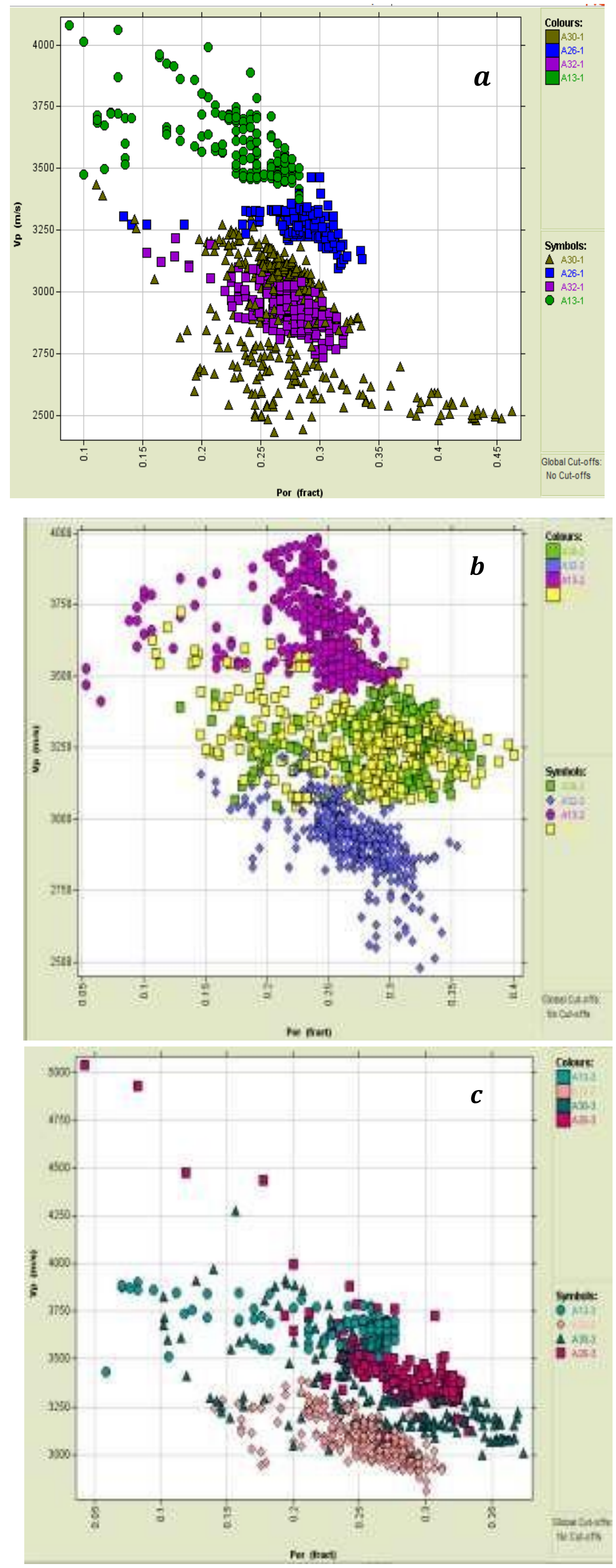

Figure 5: Vp vs Por crossplot for (a) zone 1, (b) zone 2 and (c) zone 3, in all wells

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clustering between zone A13-1 and A26-3, it also shows similarity in the disposition of the data points to an imaginary regression line passing through them, to highlight the relationship between Vp and porosity (b) shows very good overlap between zones A 26-3 to A30-3, (c) highlights the geologic equivalence between A26-4 and A30-4, by the overlap of the data clusters and the disposition of data points from the zones to the relationship between Vp and porosity., shows the clustering of zones A30-1 and A32-1, indicating the similarity of their geologic properties.

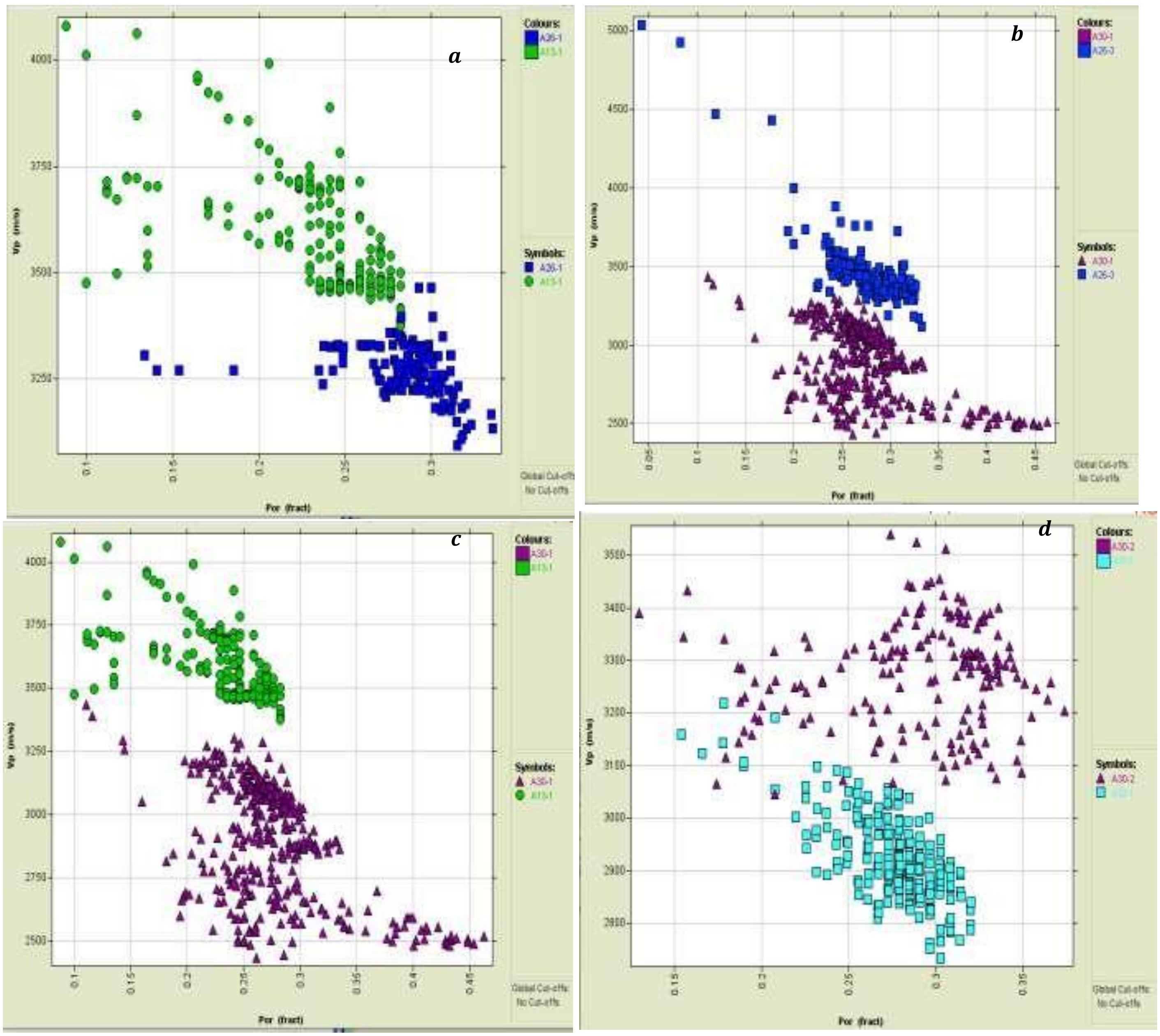

Figure 6: Vp vs Por crossplot for typically geologically unrelated sand zones

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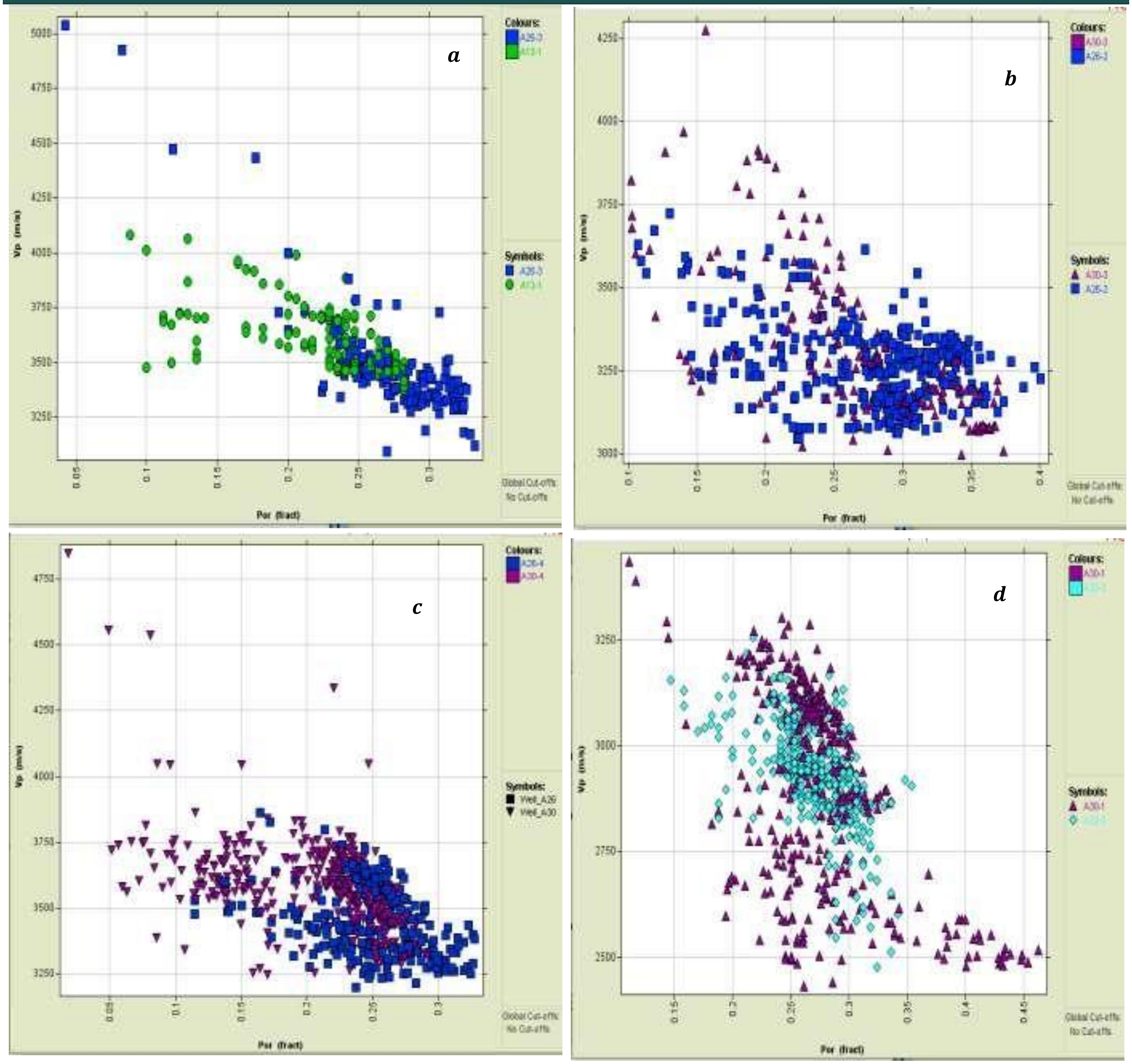

Figure 7: Vp vs Por cross plot for typically geologically related sand zone

Figure 8, shows the well correlation panel where lithostratigraphic units have been linked throughout the wells, based on the semblance observed on the rock physics diagnostic cross plot space. Using the bulk modulus (K) against porosity diagnostic plot (Figure 9), the correlation is given some validation as the data point clusters show very good overlap and relational similarity in terms of the variation between K with por. This novel rock physics diagnostic model approach to well correlation is employed, on the premise that; rock physics diagnostic models being indicative of rock texture, depositional environment and diagenetic history (Avsth et al., 2010), must be robust at identifying specific laterally continuous sedimentary units, which though may be disjointed spatially, should retain their textural and historical characteristics, and as such should aid their identification and matching across multiple wells. Particularly when the effects of other factors, such as pore fluid saturation are suppressed by fluid substitution, to ensure that the observed diagnostic

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properties - elastic moduli and velocities, are principally rock matrix based.

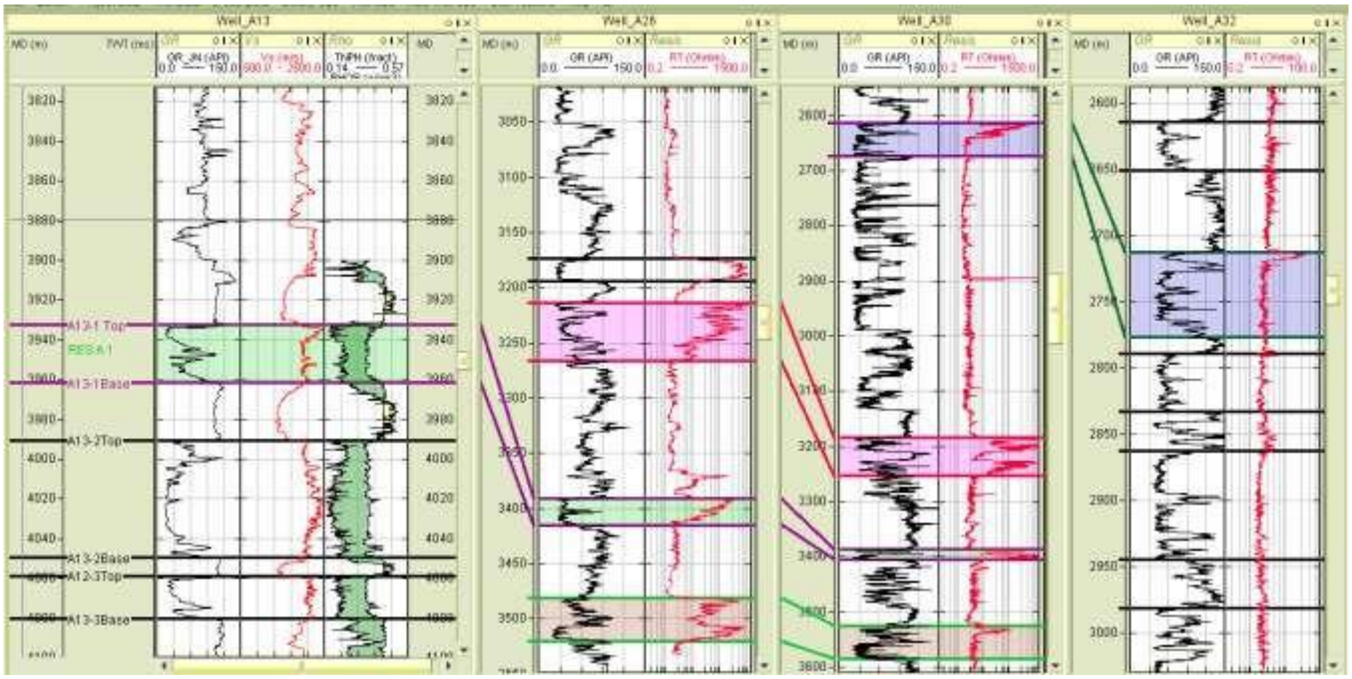

Figure 8: Well correlation panel showing the correlation of lithostratigraphic units across wells based on observed semblance in the rock physics diagnostic space

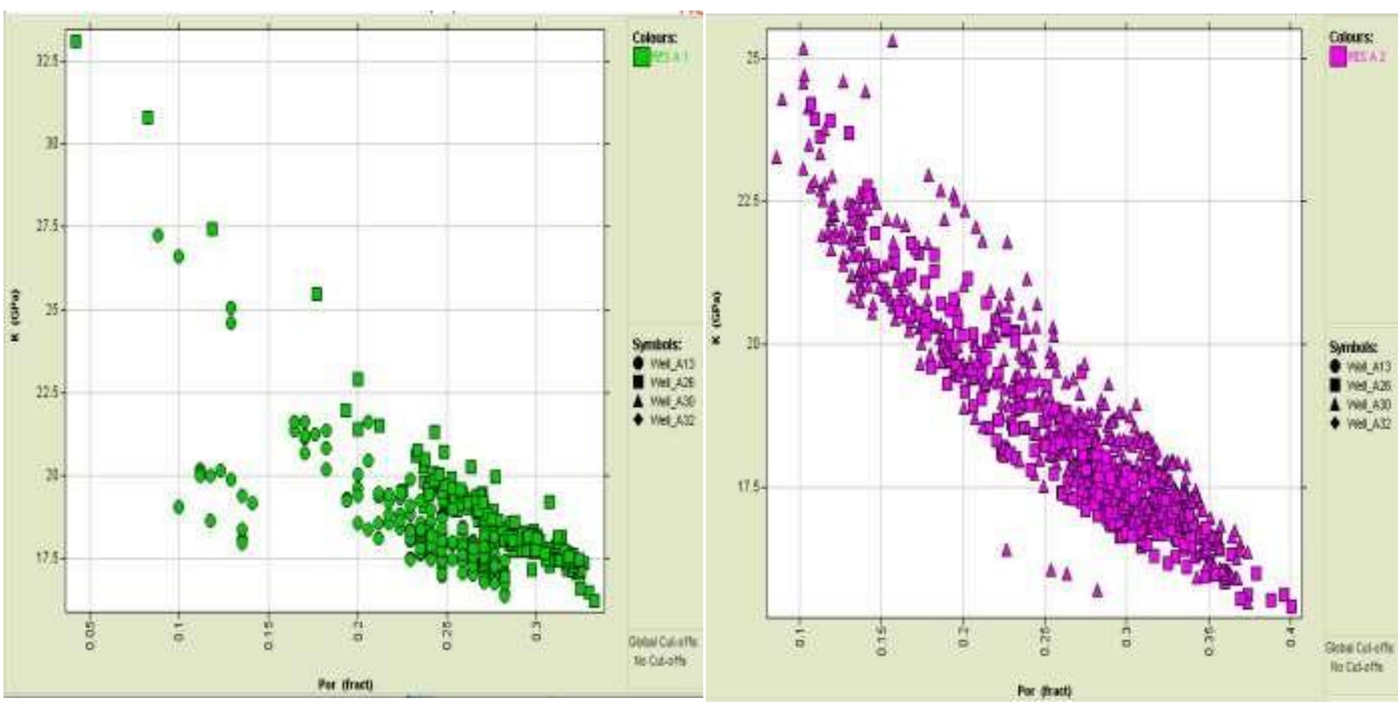

Figure 9: K vs Por diagnostic plot showing good overlap for typical zones correlated across wells.

The analyses of the emblance carried out here has been purely qualitative, by visual inspection of the spatial distribution of the data points on the diagnostic cross plot plane, as a first pass of this novel application of rock physics diagnostics for well log correlation. However, it can be made more detailed, statistical and quantitative, such that the actual regression relation for the zones are considered in conjunction with existing templates and other statistical schemes to establish the similarity between the sand zones. The technique may be validated also, by the use of biostratigraphy data, where available. The technique has promise for integration, as results obtained by it, can serve as the model input to the evolving artificial intelligence (AI) schemes already being employed, to both reduce the subjectivity, time loss and manual effort involved in this technique on its own and give more geologic basis to the AI schemes.

4 CONCLUSION

The application of rock physics diagnostic models, which highlight the link between relational trends of elastic moduli or velocities with porosity to rock geologic history and texture, to well log lithostratigraphic correlation has been investigated in this endeavour, as a novel technique for achieving this rudimental reservoir characterization task of establishing chonostratigraphic equivalents within different wells. This outlines the first pass application, from which it can be concluded that well log correlation, which can be challenging process in frontier settings, where geologic constraints may not be readily available, can be confidently achieved by employing the rock physics diagnostic scheme. Although the technique is yet subjective, labour intensive and needs to more refining.

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