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RESEARCH ARTICLE

PREDICTION OF POROSITY OF RESERVOIR SANDS USING SEISMIC ATTRIBUTES IN "ARIKE" FIELD NIGER DELTA, NIGERIA

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ABSTRACT

The study aimed at predicting the porosity of reservoir sands in 'Arike field' Niger Delta, Nigeria by converting seismic trace of the interval of interest in the seismic survey into a porosity log to generate a porosity volume. Optimal number of relevant attributes were selected using multi-attribute analysis. The study discovered that three attributes (energy, velocity fan, and Q factor) were efficient. These attributes were then utilized to train a supervised neural network to establish the relationship between seismic response and porosity. The Opendtect software used, extracted all specified input attributes and target values over the specified range along the well tracks and randomly divided the data into a training and test set attribute. The study established the integration and correlation of energy attribute, velocity fan attribute, and Q factor as relevant seismic attributes for porosity estimation when little or no well log is available, hence giving a means of spatially extending well data.

KEYWORDS

Seismic, Porosity, Well logs, reservoir characterization.

1. INTRODUCTION

Exploration leads to the discovery of petroleum, which includes delineation of reservoirs, followed by the development of the field, and production by primary, secondary, and tertiary oil recovery (Ahmed and Meehan, 2012; Satter and Iqbal, 2015; Kafisanwo et al., 2018, Falade et al., 2021; 2022). Uncertainties in oil and gas supplies and unstable prices often lead many companies to focus on increasing their reserves through more precise definition and detailed characterization of reservoirs within oil fields. Predicting hydrocarbon reservoir properties is important in the determination of the hydrocarbon reserves, their recoverable portion, their flow rate, prediction of future production, and how the production facilities will be designed (Olatunji, et al., 2011; Kafisanwo, 2019). Porosity among other petrophysical parameters is fundamental in assessing different possible scenario within a reservoir and its prediction can be accomplished using 3-D seismic data and well logs (Bosch et al., 2010).

Some specific measures of seismic attributes derived from seismic data includes geometric, kinematic, dynamic and statistical features (Chopra and Marfurt, 2006; Sarhan, 2017; Hossain, 2020). A certain number of attributes like measures of reflector time, reflector amplitude, the energy between formation top and bottom, formation thickness, reflector dip and azimuth, illumination, complex amplitude and frequency, amplitude versus offset, coherence, and spectral decomposition are classified as general attributes (Pennington et al., 2001; Chopra and Marfurt, 2005; Subrahmanyam and Rao, 2008; McBride et al., 2013; Abdul Khalid et al., 2016). Seismic Amplitude is noted to be the main factor for extracting physical parameters such as the reflection coefficients, acoustic impedance, absorption, velocities, etc. (Taner, 2001; Das et al., 2017).

Numerous researchers like (Doyen, 1988; Schultz et al., 1994a, 1994b; Taner, 2001; Chopra and Marfurt, 2005; 2006; 2007; Banerjee and Salim, 2020) etc. have worked on seismic attributes analysis to reveal quality information about the physical parameters and subsurface geometry. Provision of detailed and correct information on lithostratigraphic and structural parameters of the seismic prospect is the overall intent for analyzing the attributes (Ogiesoba, 2010; Devalla, 2013; Hart, 2013; Anomneze, et al., 2015). Therefore, porosity prediction using seismic attributes will be efficient in determining the vertical and lateral distribution of porosity within the reservoir which a point data (well log) only cannot reveal.

Neural network is an efficient techniques applied to deal with extreme levels of heterogeneity (Mori and Leite, 2018). Neural networks are made up of a lot of highly interconnected processing units (neurons) working together to solve specific challenges (Christos and Dimitrios, 1996). Correlations between point data (well log) and spatial data (seismic) are frequently made using the neural network method. Therefore, the approach is adopted in this study for porosity prediction. The application of neural networks for multi-attribute analysis has revealed reservoir features necessary for hydrocarbon exploration. The best parameters that can be used as input for a better prediction accuracy using neural network method are multi-attributes from the integration of well data and seismic data.

The objectives of this study are to delineate reservoirs and estimate porosity from well logs and determine the lateral and vertical distribution of porosity that can be used to guide developmental drilling and the aim is to predict porosity of the reservoirs in an oil Field ("Arike") using 3-D seismic data, well logs and neural network. The findings from this study will be used as a guide for oil field appraisal, development and

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hydrocarbon recovery (Dorrington et al., 2004; Soubotcheva and Stewart, 2004; Ogiesoba, 2010; Olowokere, 2011; Abdulaziz, 2020; Soleimani et al., 2020). This study was conducted to establish the relationship of porosity with some seismic attributes, which provides a way of extending point data into a seismic scale and create a way of estimating porosity in the absence of well logs. The application of neural network in predicting porosity will eventually improve reservoir characterization when well log data is not available.

2. Location and Geomorphology of the Study Area

The field under investigation lies within onshore Niger Delta in southwestern Nigeria. The Niger Delta is situated in southern Nigeria between latitudes 4^0N and 6^0N and longitudes 3^0E and 9^0E as shown in Figure 1 (Nwachukwu and Chukwura, 1986).

2.1 Regional Geologic Setting of Niger Delta

Niger Delta, situated on the Gulf of Guinea in the West Coast of Central Africa is a sedimentary basin which is structurally controlled by lineaments resulting from the opening of the South Atlantic Ocean (Knox and Omatsola, 1989). The continental Basement is evident by two structural elements; a NE-SW and NW-SE systems defining the northwestern and northeastern edge of the basin respectively (Murat, 1972). The former is termed Benin hinge line and the latter Calabar hinge line. The basin is also delimited in the north by the Anambra Basin. Marine sediments started accumulating in the basin in the Albian time, after South Atlantic Ocean opened between the South American and African continents (Murat, 1972). The Late Paleocene/Eocene accounted for the development of true delta through building out of sediments beyond troughs between basement horst blocks at the northern flank of the present delta area.

The delta plain has ever since prograded southward by steadily assuming a convex -to- the sea morphology in the oceanic crust. Throughout the geological history of the delta, the interplay between rates of subsidence and sediment supply has been controlling its structure and stratigraphy (Doust and Omatsola, 1990). The climatic variations and eustatic sea-level changes have influenced sedimentation rate in the hinterland while the initial basement morphology and differential sediment loading on unstable shale controls the subsidence. Most reservoirs currently producing are mainly beach, shoreface, channel sands and occasionally in the distal portions of the delta system are the turbidite sands all in the Akata Formation. The trap and seal formation is tectonically controlled by gravity within the delta. The most favourable exploration target so far has been structural traps while stratigraphic traps are being looked up on to harbour more important targets in distal and deeper portions of the delta (Michele et al., 1999).

3. Materials and Methods of Study

3.1 Materials

The database comprised 3D seismic reflection lines covering a field of about 288 km^2, borehole logs from four wells, velocity check shot survey data and a base map showing the distribution of the wells. Petrel™ and Opendtech™ Software with a dedicated workstation were used.

3.2 Methods of Interpretation

3.2.1 Base Map of the Study Area

The base map (Figure 3) shows the distribution, orientation and location of the various data sets. The map is composed of 3D seismic lines, drilled wells, direction of north, linear scale and a legend showing the status of the drilled wells.

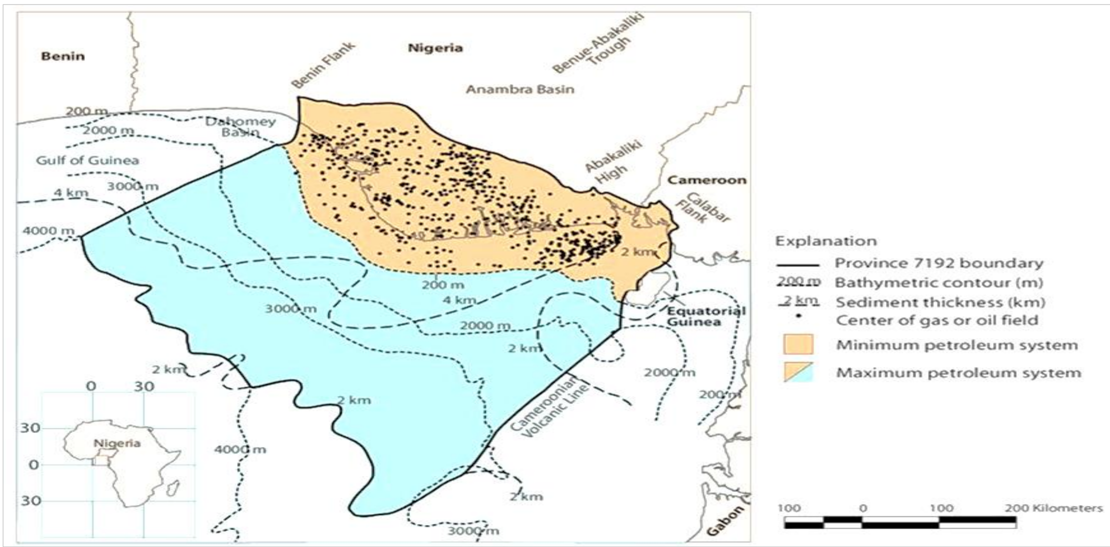


Figure 1: Southern Nigeria Showing the Niger Delta (Petroconsultants, 1996)

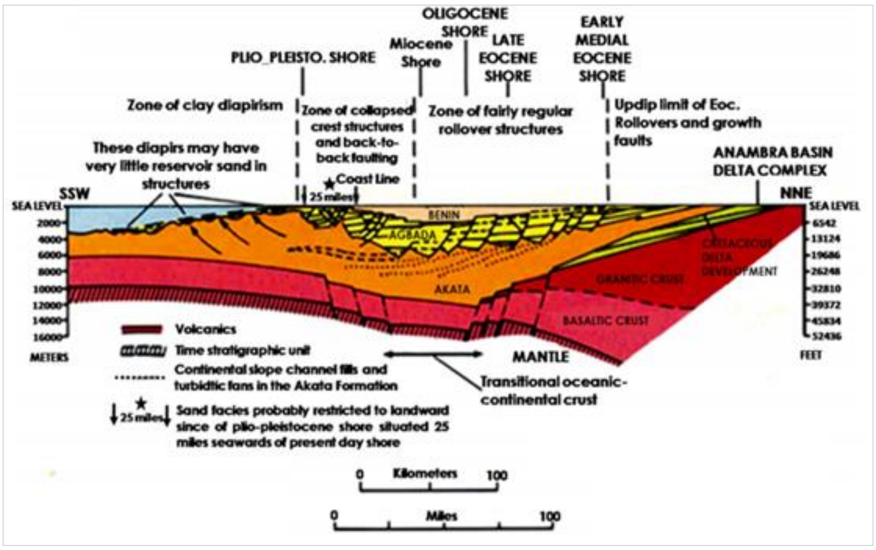


Figure 2: Schematic Dip-Section of Niger Delta with the Three Lithofacies Units, (After Whiteman, 1982).

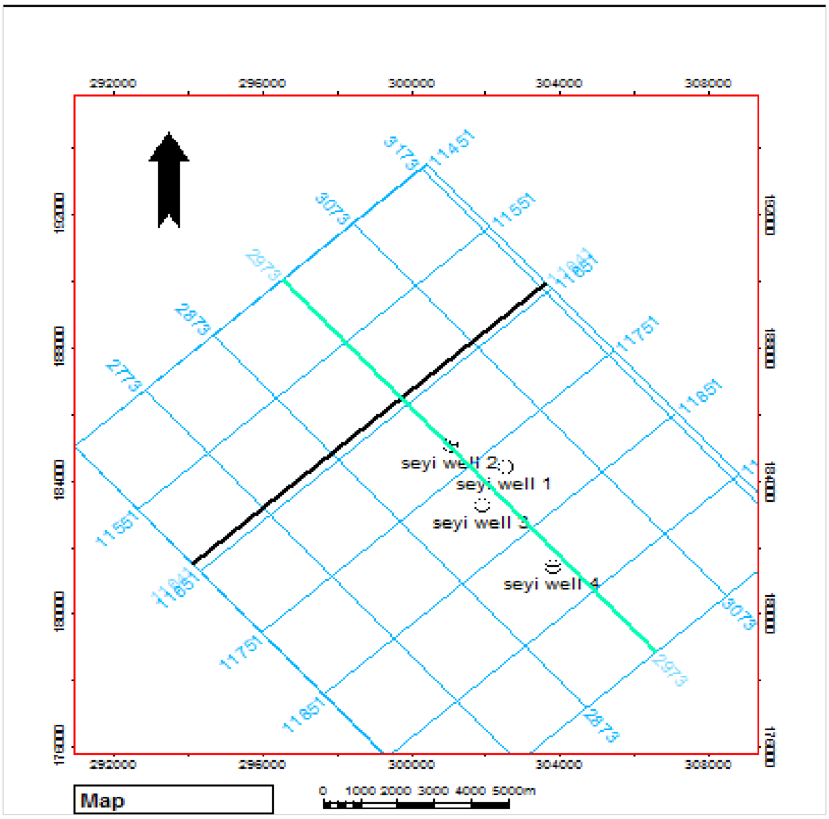


Figure 3: Base Map of Field "ARIKE" Showing the Positions of the Four Wells with the Inlines and Crosslines

3.2.2 Formation Evaluation

The well log interpretation involves extraction of qualitative and quantitative information from geophysical well logs and the computation of petrophysical parameters was accomplished by the transformation of the measured log data into the required formation parameters through the use of standard petrophysical relationship (Asquith and Gibson, 1982). Interpreted well logs are used in delineating physical rock characteristics like porosity, volume of shale, lithology and identification, determination of depth and thickness of and hydrocarbon bearing zones.

Example of Petrophysical Parameter Calculation for Sand 1 _Well 1 (Depth interval, 1341.83 - 1360.1 m):

Volume of shale (V^{sh}) Using Larionov model

$$v_{sh=0.083(2^{3.7}\times I_{GR-1.0})} \text{ (Larionov,1969)} \qquad (1)$$

$$v_{sh=0.083(2^{3.7}\times 0.26_{-1.0})} = 0.02$$

Where,

v_{sh} is the volume of shale

I_{GR} is the gamma ray index

And

$$I_{GR} = \frac{GR_{log} - GR_{min}}{GR_{max} - GR_{min}} \ (Larionov, 1969) \qquad (2)$$

Where,

GR_{max} is gamma ray maximum (shaly sand)

GR_{min} is gamma ray minimum from clean sand

GR_{log} is gamma ray log (shaly-sand)

GRmax = 95

GRmin = 30

GR log = 47

$$I_{GR=\frac{47-30}{95-30}}$$

$$= 0.26$$

Porosity from density log using matrix and fluid densities according to Halliburton, 1991.

$$\emptyset = \frac{\rho_{ma-\rho b}}{\rho_{ma-\rho fl}} \qquad (3)$$

$$\frac{=2.65-2.63}{2.65-0.74}$$

$$= 0.2$$

Effective porosity

$$PhiE = \emptyset_{T-V_{sh}} \qquad (4)$$

$$= 0.2 - 0.02$$

$$= 0.18$$

Where Φ = porosity, ℓ_{ma} = matrix density, ℓ_b = formation bulk density, ℓ_{fl} = fluid density,

PhiE = Effective Porosity (%)

3.2.3 Synthetic Seismogram

The density and sonic logs were used and combined based on their availability to obtain the reflectivity and impedance, the output of the impedance and reflectivity was convolved with the wavelet gotten from the 3D seismic volume. This was done with a view of establishing a relationship between well information and seismic data. This is also to effectively correlate the reservoir sands picked on well log to seismic horizons in order to build a structural-stratigraphic interpretation.

3.2.4 Attributes Analysis

Seismic attributes give an idea of the vertical - lateral variations of the reservoirs in the subsurface. The attempt to predict porosity was undertaken after completing the horizon and fault mapping. In this study, the optimal number of predicting attributes were selected using multiattribute analysis. The selected attributes were then used to train a supervised neural network. Combinations of three attributes were found to be effective in predicting porosity (Energy attribute, velocity fan attribute and Q Factor attribute).

The instantaneous amplitude accounts for the reflectivity strength, which is directly related to the square root of the total energy of the seismic signal at a short period of time. Therefore, energy attribute is the square of amplitude and this represents the acoustic impedance contrast that is used to monitor alterations in lithology (Azeem et al., 2016; Omoja and Obiekezie, 2019). The amount of residual energy in a seismic wave when it leaves a rock medium is estimated using instantaneous quality factor (Q). Instantaneous quality factor (Q) is important as it helps to estimate the residual energy when a wave penetrates a medium and the medium absorbs part of the energy (Li, 2012). The ratio of the energy left to the initial energy in held in the wave is known as the instantaneous quality factor (Q) (Gardner et al., 1978). Velocity fans filter releases energy with apparent velocities for surveys in time and/or depth domain inside a specified range. Therefore, velocity fans filter can be used to enhance certain event (Pennington et al., 2001; Chopra and Marfurt, 2007).

3.2.5 Neural Network and Porosity Prediction

Neural network is primarily applied to handle the non-linear relationship between information from seismic and well log data. In this study, the three attributes (Energy attribute, Velocity fan attribute, and Q Factor attribute) were subjected to supervised neural network analysis in order to establish the relationship between seismic response and porosity for porosity prediction. The way neural network was applied for multi attribute analysis in this study is shown in figure 4 and figure 5 depicts the supervised neural network structure that was used.

Exporting sub-volumes for all three attributes is the first step in the process of building the input training set for the supervised neural network. In this study, the data was randomly divided into a training set and a test set attribute using the Opendtect software, which also extracted all specified input attributes and target values over the specified range (Random line) along the well tracks. The iterative training performance and the relationship between network outputs and targets were monitored. After training, the trained network parameters were applied to the entire data set (attributes at non-well locations) to predict porosities for the entire study area. The flowchart for the methodological approach adopted is shown in figure 6.

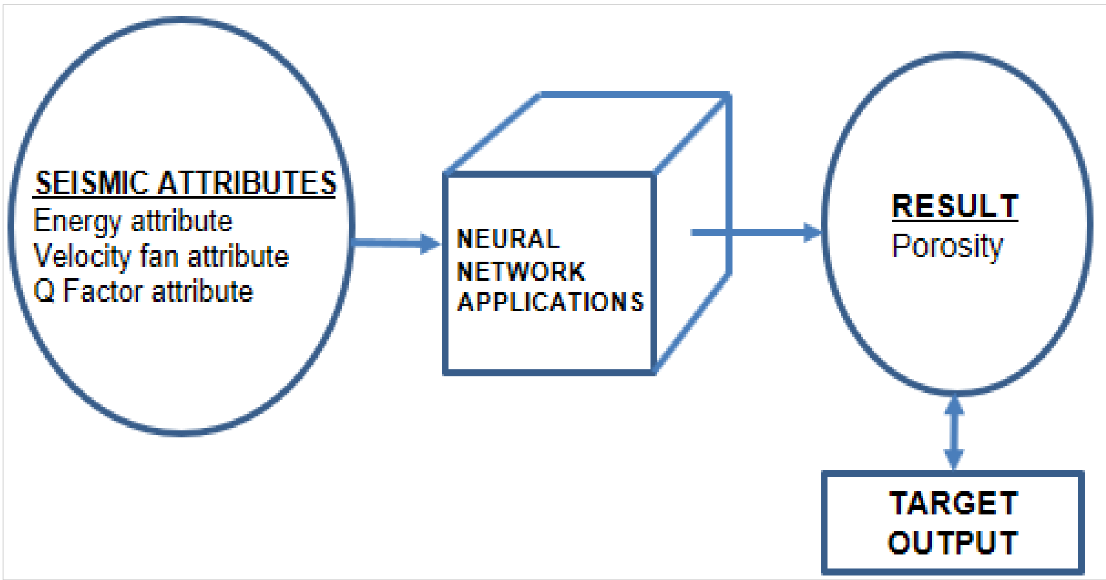


Figure 4: Schematic Representation of Neural Network Algorithms for Multi-Attribute Analysis.

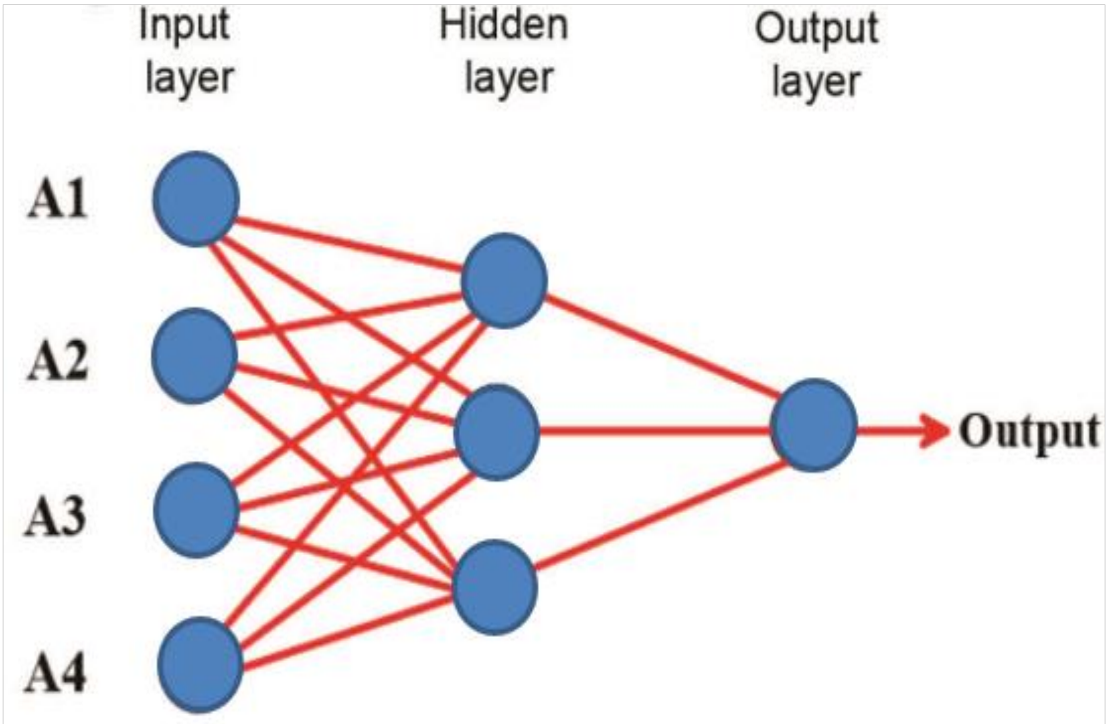


Figure 5: Architecture of Neural Network

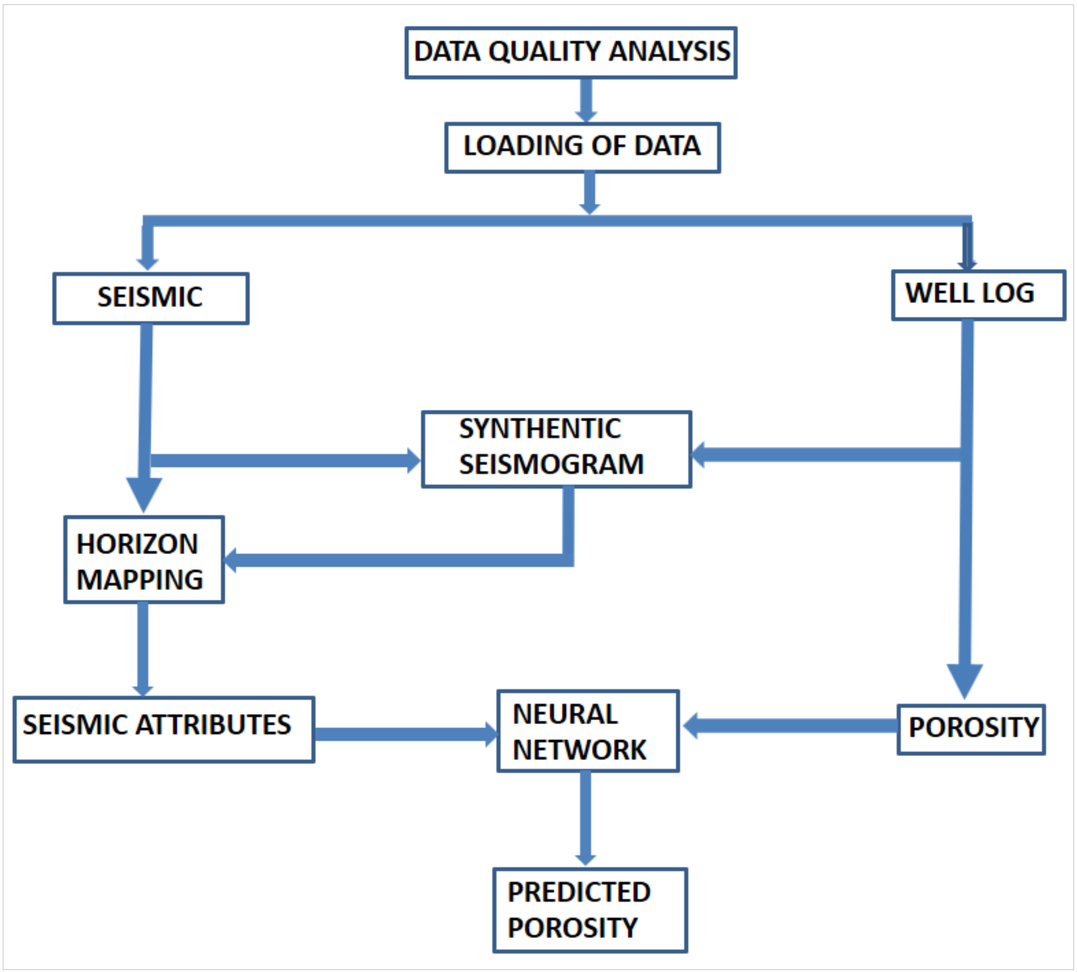


Figure 6: Flowchart of the Methodology Implemented in the Present Study

4. RESULTS AND DISCUSSION

Results of this research work focus on the relationship between attributes, porosity distribution seismic and neural network to proffer solution to the exploration problems such as prediction of effective porosity in hydrocarbon reservoirs viz development of more wells and production planning. Results obtained from this research are presented as table, graph, cross-sections, well correlation panel time maps, depth maps and attributes maps for further analysis.

4.1 Porosity from Well Log

The sand bodies delineated in the wells were correlated in NW – SE direction and the correlation panel is as displayed in Figure 7. Their average porosity computed for all the sand bodies identified ranges between 0.2 – 0.35 as seen in table 1.

4.2 Synthetic Seismogram Generation

The synthetic seismogram shows a better connection between the seismic section and well log. The combination of density and sonic logs gives acoustic impedance and reflectivity. Each horizontal signal line on seismic section represents the amplitude strength, the output of the log signature and seismic section gives event on seismic that are correspondent to geologic formation on well log. The output is a synthetic seismic trace for Arike well 4 as shown in Figure 8. Horizons 1-7 were matched with the seismic trace extracted in the volume along well path so as to ensure correct interpretation with the process started from the known to the unknown. Both composite seismic and synthetic traces were cross-correlated to get an indication of the alignment and matching quality as an output value. There was little or no need for alignment of the seismic traces and the synthetic since there was little or no difference in the travel time.

4.3 Neural Network and Seismic Attribute Analysis

The results of the study from the horizontal sections demonstrated the spatial distribution of porous zones on the horizons by applying neural networks for each horizon that was mapped using each attribute separately before combining them, as shown in figures 9 to 15. The porosity predicted using the seismic attributes one by one has a weak relationship with the porosity and is insufficient for more accurate prediction. The maps were interpreted using the colour bar. Energy attribute has five colour codes ranging from high to low. An area with colour pink, blue and orange shows high porosity zones whereas an area with lemon green and yellow shows low porosity zones. Q factor attribute has three colours, dark colour and light orange indicates high porosity zones, whereas deep red colour indicates low porous zones. Also velocity fan attribute has three colours, deep red and orange colour depicts porous zones while dark colour shows low porous zones. The energy, Q factor, and velocity fan attribute combination was found to be the best combination for porosity prediction by the trained supervised neural network. Pockets of porous zones scattered across the surface are characterized by high energy, high Q factor and low velocity which depict an excellent correlation with high porosity zones

4.4 Porosity Prediction

The horizontal and vertical section in figure 9 – 15 shows the predicted porosity volume of all the mapped horizons and figure 16 for the entire field on a random line. The result was obtained using application neural networks to the seismic attributes generated from the seismic volume. The porosity value ranges between 20% and 38%. The porous zones on the porosity maps are ranked high, medium and low. Hot colour red and yellow is indicating areas with high porosity values while blue colour denotes low porosity values as shown in Figures 9 to 15 for all the horizons mapped and figure 16 for the vertical section. It is observed through the slices that porosity distribution decreases along fault zones and also as the depth increase porosity tends to increase which suggest a possible overpressure zone or under compaction. Similar deduction has been made on the lateral section and these results appear to agree. This result can be used to assess the scenario with the reservoirs as regards production. It was again observed that the already drilled well falls within the zones of high porosity implying the targeted structures are amplitude

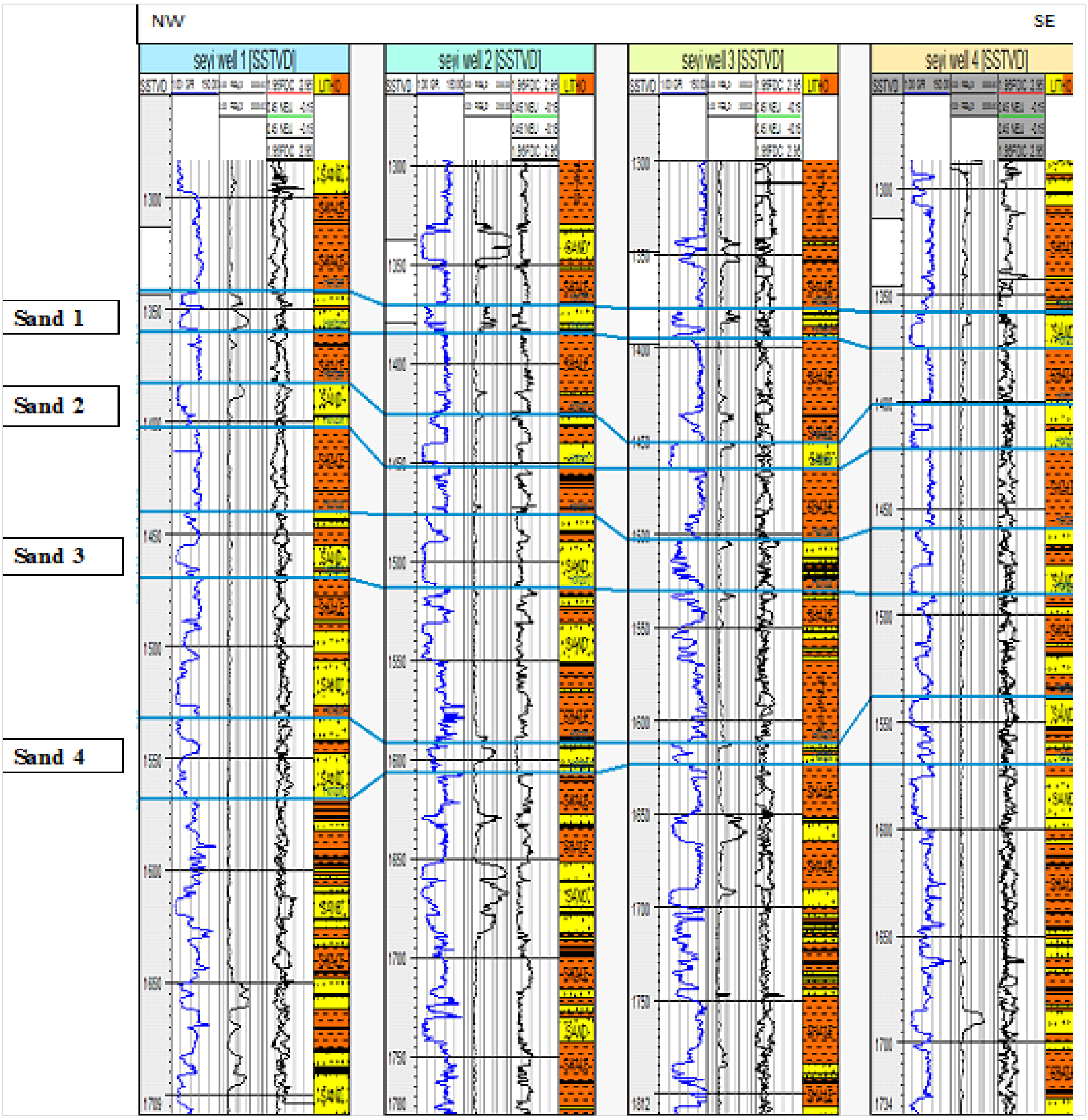


Figure 7: Well Correlation Panel of "ARIKE" Field

Table 1: Summary of Petrophysical Parameters Computed for the Wells

	Reservoir Sand	Thickness (m)	V_{shale} (%)	Total Ø (%)
Well 1	Sand 1	18	2	20
	Sand 2	20	5	26
	Sand 3	91	3	22
	Sand 4	80	3	23
Well 2	Sand 1	14	2	30
	Sand 2	11	4	35
	Sand 3	115	4	21
	Sand 4	21	4	34
Well 3	Sand 1	17	4	27
	Sand 2	14	1	29
	Sand 3	109	7	18
	Sand 4	27	19	32
Well 4	Sand 1	17	3	27
	Sand 2	21	7	29
	Sand 3	62	5	21
	Sand 4	114	5	20

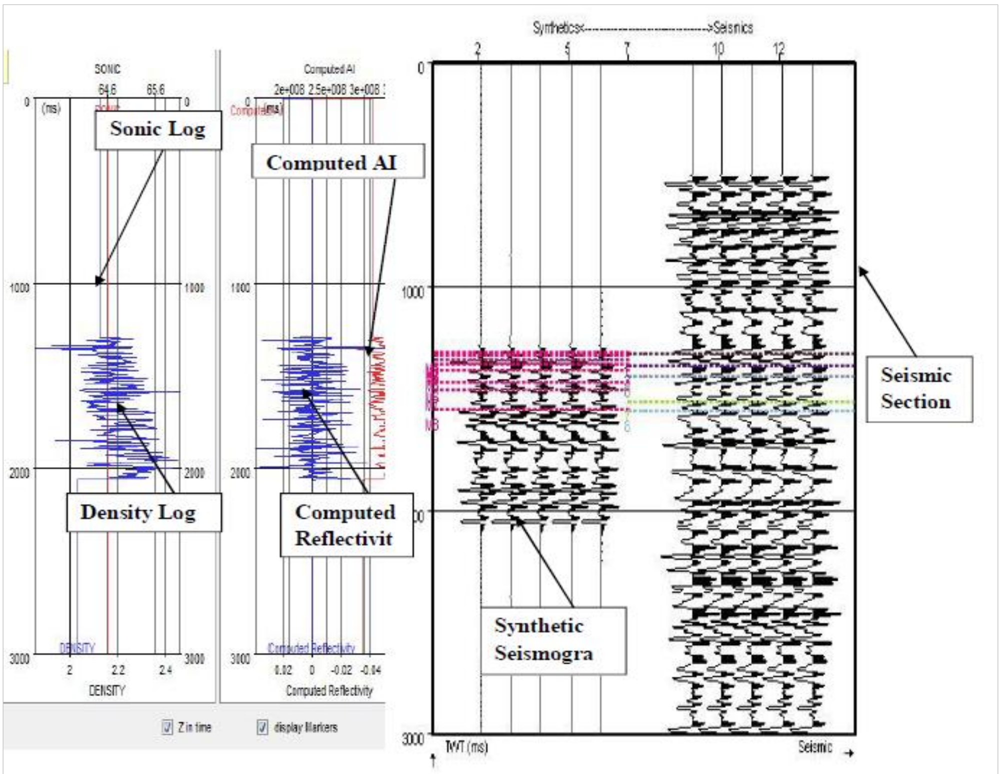
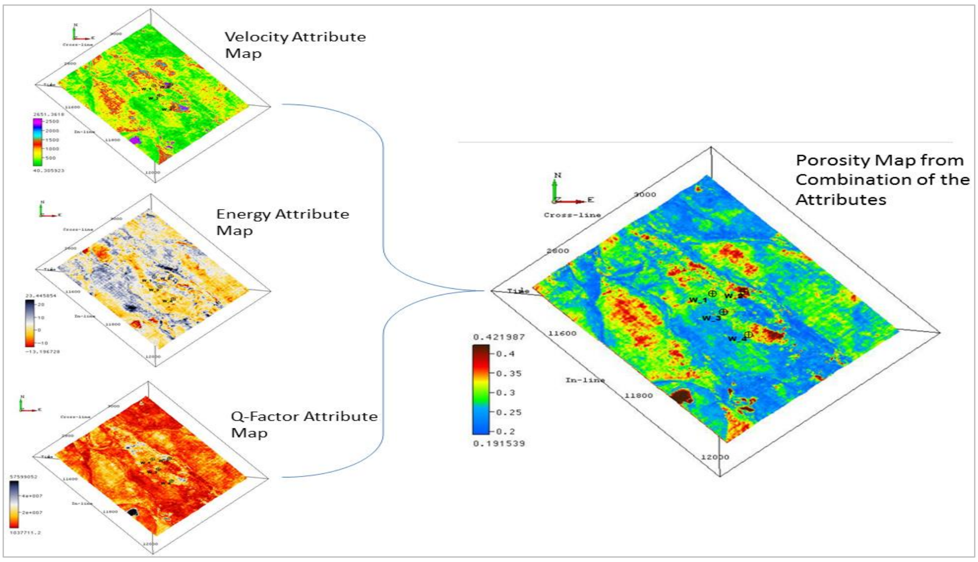
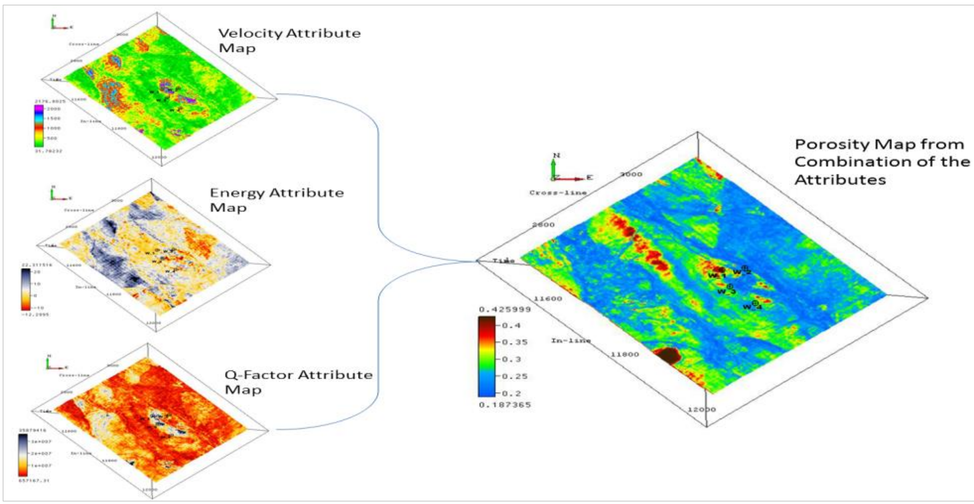


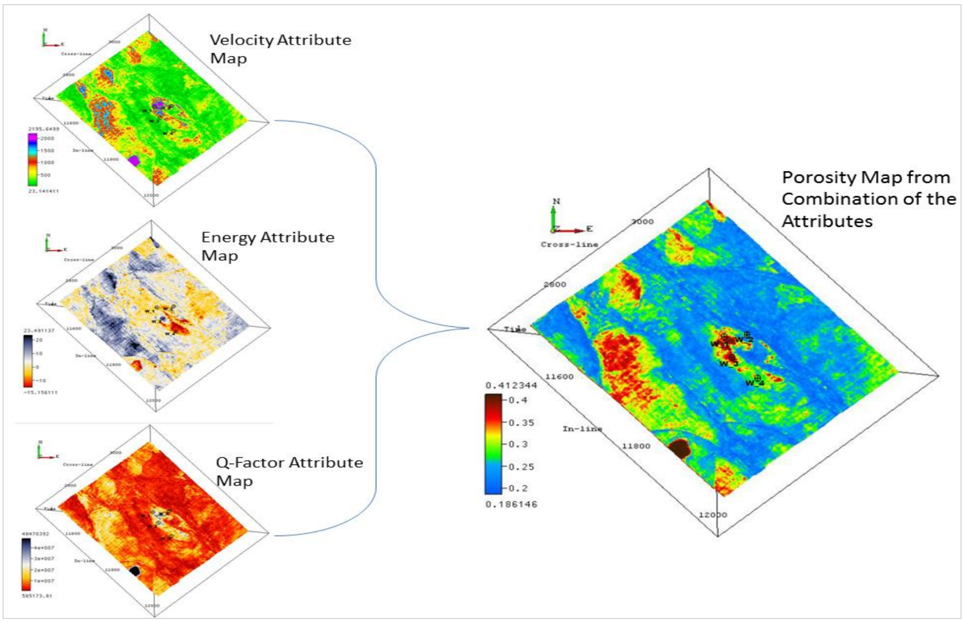
Figure 8: Synthetic Seismogram for Well 4



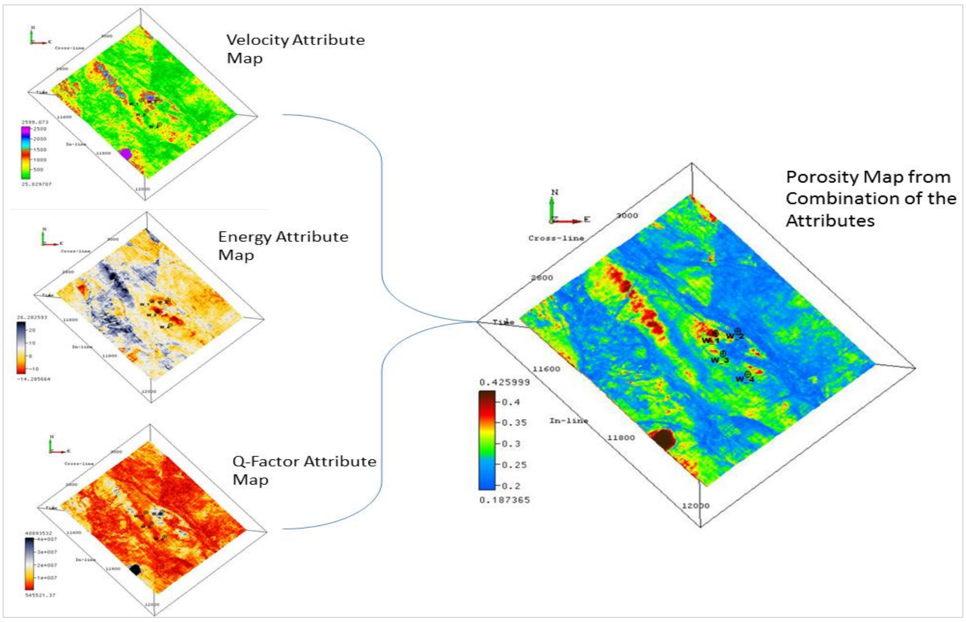
Figures 9: Attribute and Porosity Maps of Horizon 1



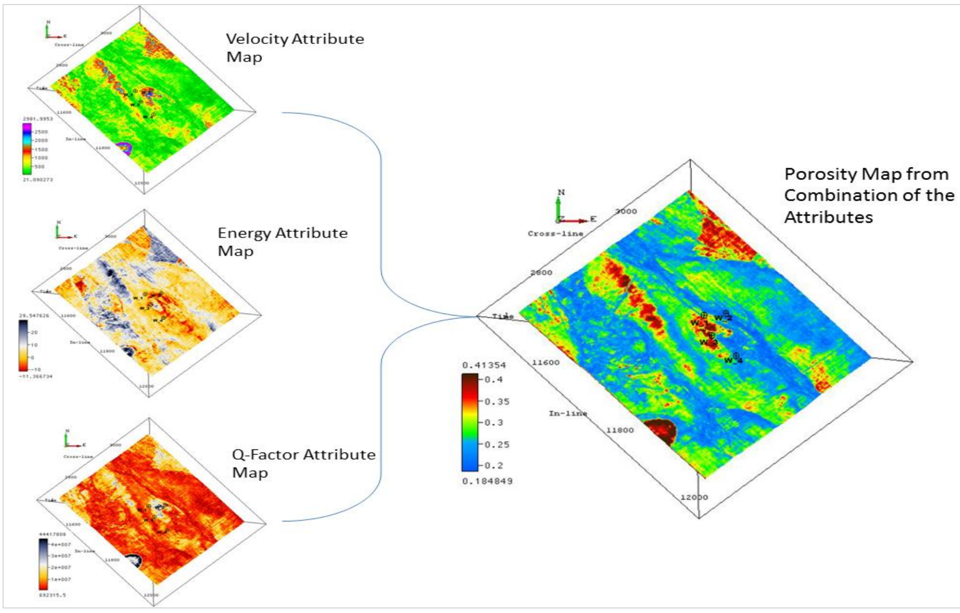
Figures 10: Attribute and Porosity Maps of Horizon 2



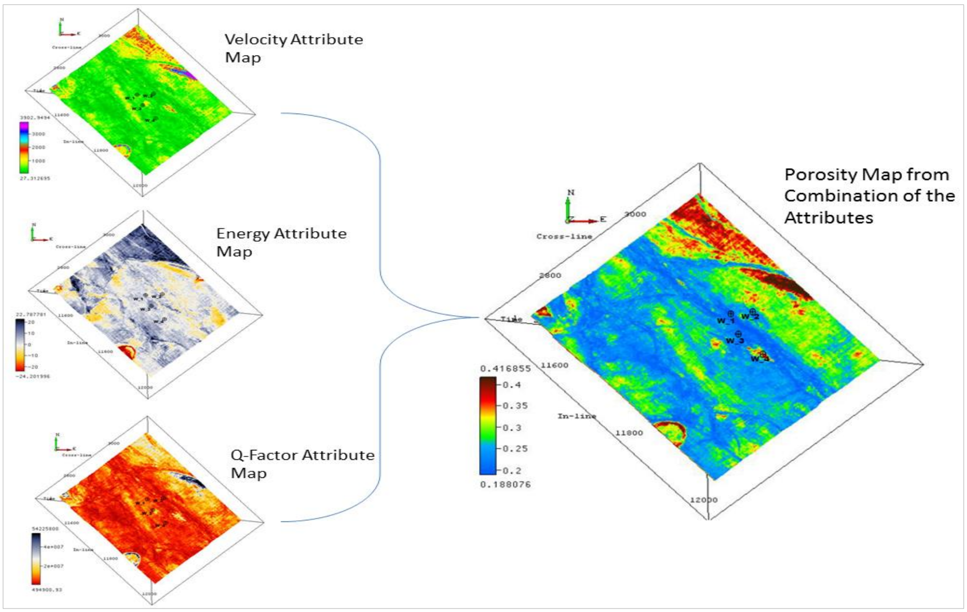
Figures 11: Attribute and Porosity Maps of Horizon 3



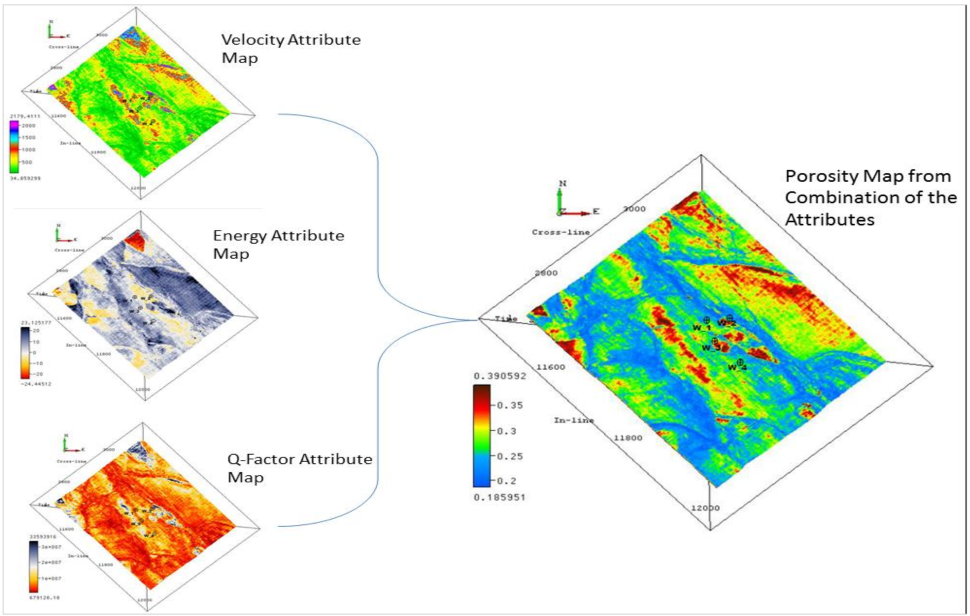
Figures 12: Attribute and Porosity Maps of Horizon 4



Figures 13: Attribute and Porosity Maps of Horizon 5



Figures 14: Attribute and Porosity Maps of Horizon 6



Figures 15: Attribute and Porosity Maps of Horizon 7

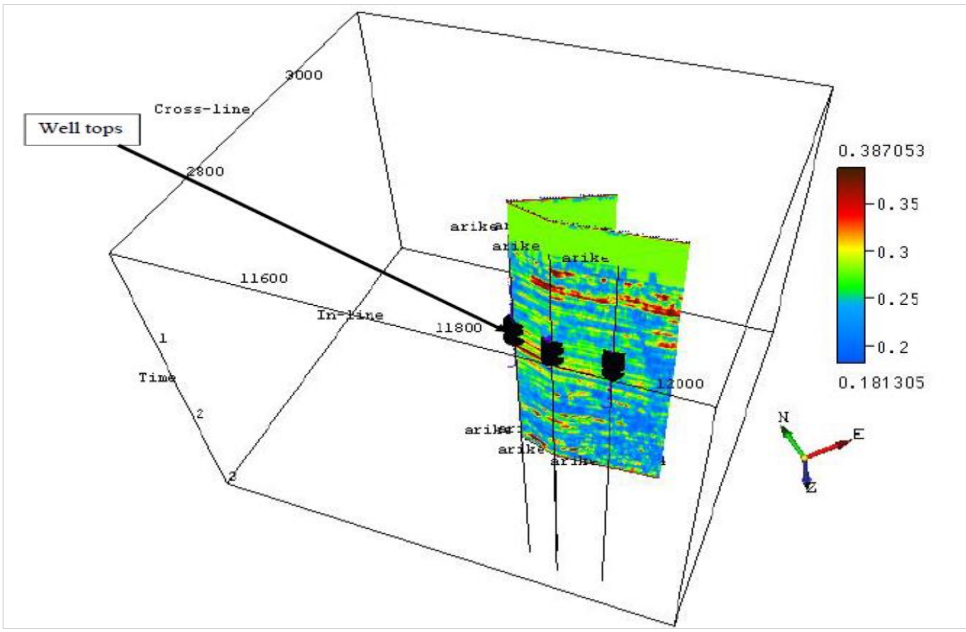


Figure 16: Porosity Map on Random Line

5. Conclusion

Four wells with porosity values ranging from 0.19 to 0.34 were used to determine the porosity in the Arike field, which had a total of 600 in-lines and 507 crosslines analysed for this study. The porosity generated from well logs were used to train the seismic attributes from seismic volume using a trained supervised neural network. Three attributes (energy, Q factor, and velocity fan attribute) were combined to generate maps, which show pockets of high porosity dispersed throughout the mapped horizons in the field. The pockets of porous zones in this study are characterized by high energy, high Q factor and low velocity. Porosity was predicted using supervised neural network on random line and the result ranges between 0.2 and 0.38 which has an excellent correlation with the determined porosity of 0.19 and 0.34. The prediction of porosity by combining different seismic attributes establishes the relationships between porosity distribution and the attributes. It is concluded that supervised neural networks are highly effective at predicting porosity when seismic attributes are combined rather than used singly. The predicted porosity from the combined seismic attributes is also established as most of the already drilled well falls within the zones of high porosity according to the predicted porosity. Thus, information extracted form seismic reveals a detailed understanding of vertical and lateral porosity distribution in the study area thus providing useful information needed for assessment, hydrocarbon recovery using neural network.

Authors Contribution

John Amigun**:** Conceptualization, Methodology, Software, Visualization, Investigation, Supervision. Florence Oyediran**:** Conceptualization, Methodology, Software, Data curation, Validation. Ayodele Falade: Conceptualization, Visualization, Methodology, Software, Validation, Writing- Reviewing and Editing.

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Conflict of Interest

The authors declared that they have no conflict of interest.

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