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Prediction of petrophysical properties through comparative post-stack inversion techniques using advance Neural Networking

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Abstract

The sophisticated seismic inversion methodology develops the relationship between the interpreted seismic data and the elastic properties to discerning the desired facies in the reservoir characterization. The study is focused on the C-interval sand of the Lower Goru Formation by utilizing Post-stack Time Migration (PSTM) 3D seismic and borehole logs of six wells. The challenges in the facies discrimination arise due to various complexities, i.e., lithological variability and acquisition sensitivity of recording tools. Various quantitative interpretation techniques such as Band limited inversion, Model-Based inversion, and Stochastic inversion are developed to handle the limitations effectively and precisely access the producing facies. A comparative analysis is performed for the heterogeneous sands by employing these QI techniques and evaluating their effectiveness. The inverted seismic attributes are further utilized in the petrophysical properties estimation through Probabilistic Neural Networking (PNN) algorithm to distinguish litho-facies by developing a petro-elastic relationship. Probabilistic Neural Networking works best for the heterogeneous reservoir's petrophysical properties estimation, especially sand reservoirs with shales intercalation. The concluding results declare the efficiency of all applied techniques for potential sand zones, especially the Stochastic inversion. The petrophysical properties volume of clay and effective porosity, estimated from the Stochastic inversion attribute, matched with the results of the blind well, resolute precisely the reservoir potential, and delineated the depositional environment of the three segregated sand bodies.

Keywords: Band limited inversion; Geo-statistical methods; Model-Based inversion; Probability Neural Networking; Stochastic inversion.

1. Introduction

The increase in energy demand of the world has increased the need to adopt sophisticated computational techniques to explore and produce hydrocarbons (Ehsan *et al*., 2018). The pre-and post-stack inversion of seismic data is now considered an essential tool of the modern exploration industry used for field development (Moosavi & Mokhtari, 2016; Abdulkareem, 2022). The interpretation and reliability of the inverted seismic data allow the scientists to develop the prestacked and post stacked seismic inversion techniques. This technique increases the data reliability and reduces the risks of exploring hydrocarbons, as mapping gas-bearing sand facies using conventional techniques is challenging (Osita *et al*., 2022; Shahzad *et al*., 2022). So, this combination of seismic and well log interpretation is essential to discriminate the gas and wet sand facies quantitatively (Al-Sulaimi & Al-Rawaih, 2004). The inversion technique helps generate the reservoir rock's elastic properties that indicate the hydrocarbon zones (Adesanya *et al*., 2021). For this research work, the post stacked seismic and well log data are acquired from a hydrocarbon field located in the Middle Indus Basin, Pakistan. The geological map of the study area is shown in (Figure 1). The post-stack inversion is a stable technique usually used for the model building based on the estimated impedance of the subsurface horizons. This enables the explorations to monitor the reservoir properties during the production phase of the field and aids in decision making (Pyrcz *et al*., 2014). Petrophysical properties derived from the Neural Networking technique play a significant role in determining the areas between the wells and away from the wells having good reservoir properties (Razak, 2010; Rijks & Jauffred, 1991). The present work performs the Band-limited inversion, Model-Based inversion, and Stochastic inversion. These three inversion techniques were performed and comparatively analyzed in terms of accuracy to interpret the best-suited inversion technique. The probabilistic neural networks are a technique that can be used to efficiently identify shale layers as C-interval sands of Lower Formation consist of alternating layers of sand and shale, reducing the risk associated with exploration and production in shaly reservoirs. This method will improve the strategy adopted for exploring and developing hydrocarbon fields.

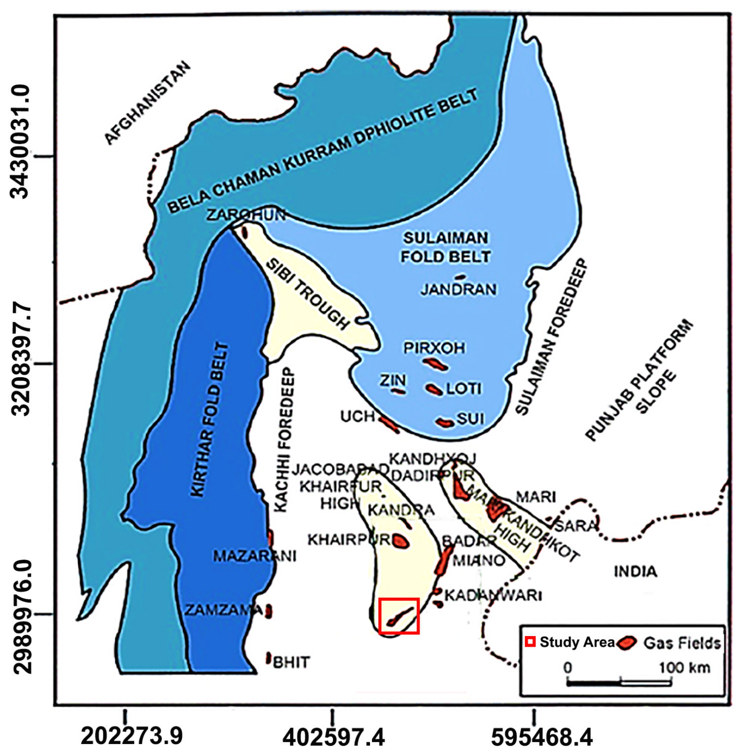

Fig. 1. Geological Map of Middle Indus Basin with highlighted Study area, Pakistan.

2. Geological Settings

The study area lies in the Middle Indus basin of Pakistan, which is a prolific hydrocarbon-bearing basin of Pakistan (Asghar, 2021; Miraj *et al*., 2021). The study area is situated in the Sukkur Rift zone along the southeastern margin of Jacobabad-Khairpur High (Zaigham & Mallick, 2000; Kadri, 1995; Kazmi & Jan, 1997; Ahmed *et al*., 2004). The geological setting of the area reveals that the Punjab Platform occupies the northeastern side. On the northern and northwestern sides, the Sulaiman Fold Belt is present. At the west of the study area, Kirthar Fold Belt is present (Miraj *et al*., 2021). Rajasthan Shelf and Indian Shield are present on the eastern side of the study area (Kadri, 1995). The prolific reservoir of this region belongs to the Cretaceous age (Afzal *et al*., 2009). The structural traps in this area were developed during the uplifting of Jacobabad Khairpur high during the Cretaceous (Quadri & Shuaib, 1986). The uplifting of the Ranikot Formation resulted in the pinch-out against the Jacobabad-Khairpur high (Kazmi & Jan, 1997).

The complete Cretaceous section of the study area is cut by a deep-rooted wrench faulting system developed due to the collision of the Indian and Eurasian plates (Burg *et al*., 2005). The hydrocarbon migration and trapping occurred during the Mesozoic and Tertiary during the crustal thrusting (Kazmi & Jan, 1997). Sembar Formation is acting as a proven source of rock in the area. The lithology of the Sembar Formation mainly consists of black shale (Khalid *et al*., 2014). C-interval sands of the Lower Goru Formation act as reservoir rock in this area. The lithology of the Lower Goru Formation comprises alternating layers of sand and shale, which depicts the deltaic environment of deposition (Berger *et al*., 2009).

3. Data and Methodology

The data for the present research has been acquired from DGPC. Data include 3D seismic volume (in SEG-Y format) survey data spanning an area of roughly 15 km^2, and well logs data from six wells lying in the vicinity were used. In this work, a variety of wireline logs were employed and interpreted. After that, post-stack inversion was done. Post-stack inversion approaches are the numerous techniques used to turn stacked seismic data into quantifiable rock physics characteristics. From post-stack inversion results only, acoustic impedance can be acquired, but Pre-stack inversion may provide acoustic and shear impedance. Some post-stack inversion methods are Band limited inversion, Model-Based inversion, and Stochastic inversion.

The advantage of this inversion is that they may combine multiple geophysical data with seismic data to improve inversion findings (Contreras *et al*., 2006). The combination of log and seismic data is used to improve the vertical resolution. The Stochastic inversion method is an initial model, and it utilizes a random Gaussian prior that encompasses the spectrum. Because input seismic lacks high- and low-frequency bands, the inversion procedure does not limit the frequency components of the original model (Varela *et al*., 2006). The workflow for performing this inversion, as shown in (Figure 3), includes extraction of wavelet, seismic tie, generating low-frequency models, petrophysical and PNN training. The probabilistic Neural Networking (PNN) technique helps manage shale packages within the sand (Khan *et al*., 2021).

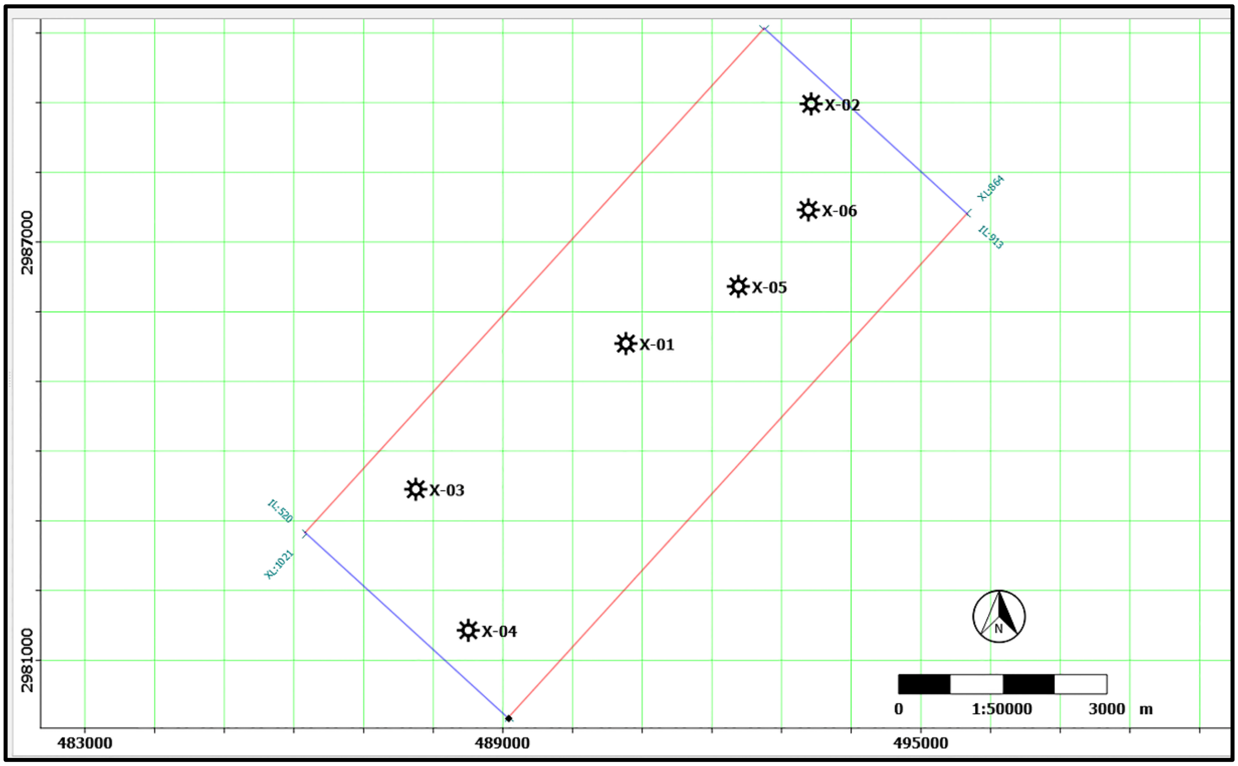

Fig. 2. Base map of the study area including wells (X-01, X-02, X-03, X-04, X-05, and X-06).

3.1 Petrophysical Analysis

The petrophysical analysis of all the wells was performed to obtain the clay volume and effective porosity values. Petrophysical interpretation of C-interval sand of the Lower Goru Formation was carried out in all wells (X-01, X-02, X-03, X-04, X-05 and X-06). The log plot of X-05 is shown in (Figure 4), where the first track is the lithology track displaying SP, Caliper and Gamma-Ray Log. The second track is known as the depth track, and it displays the depth of the well in meters. The third track represents the three resistivity logs: deep resistivity, Moderate resistivity, and shallow resistivity (ResD, ResM and ResS). The fourth track is also known as the porosity track as it displays the porosity logs, including the density log, sonic log, and neutron log. The first four tracks display the input logs, whereas the last four tracks display interpreted logs. The volume of clay is displayed in the sixth track showing the Lower Goru Formation. In the fifth interpretation, average/total porosity has been displayed. The average neutron-density porosities are used for the determination of average porosity. Effective porosity was displayed in the seventh track, calculated from the total porosity. In the last track, the water saturation of the Lower Goru Formation is displayed. Water saturation was calculated using the Indonesian equation.

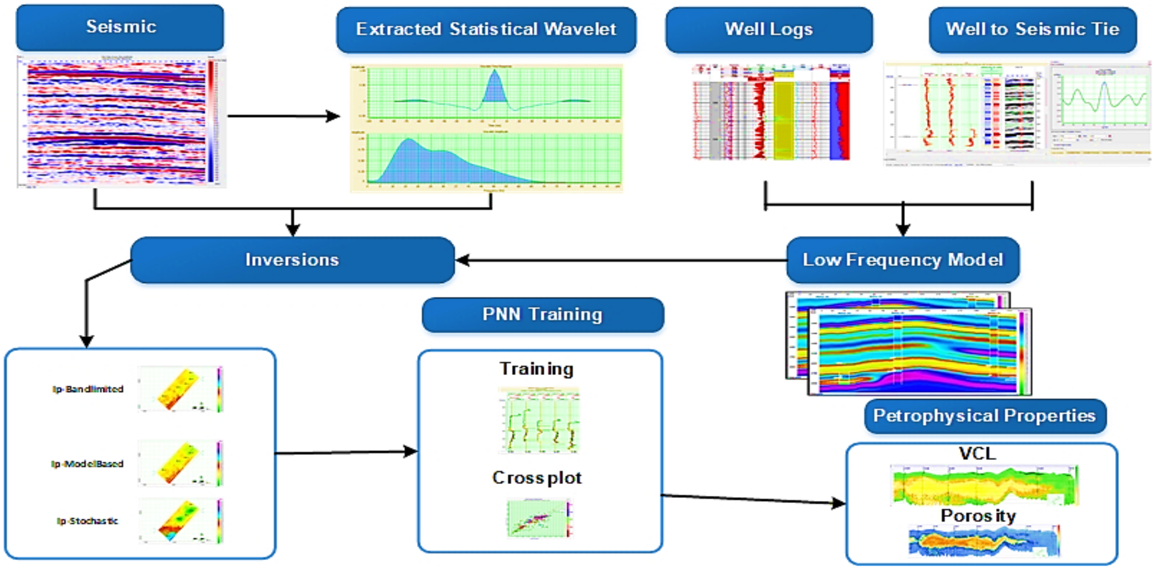

Fig. 3. Workflow for the study.

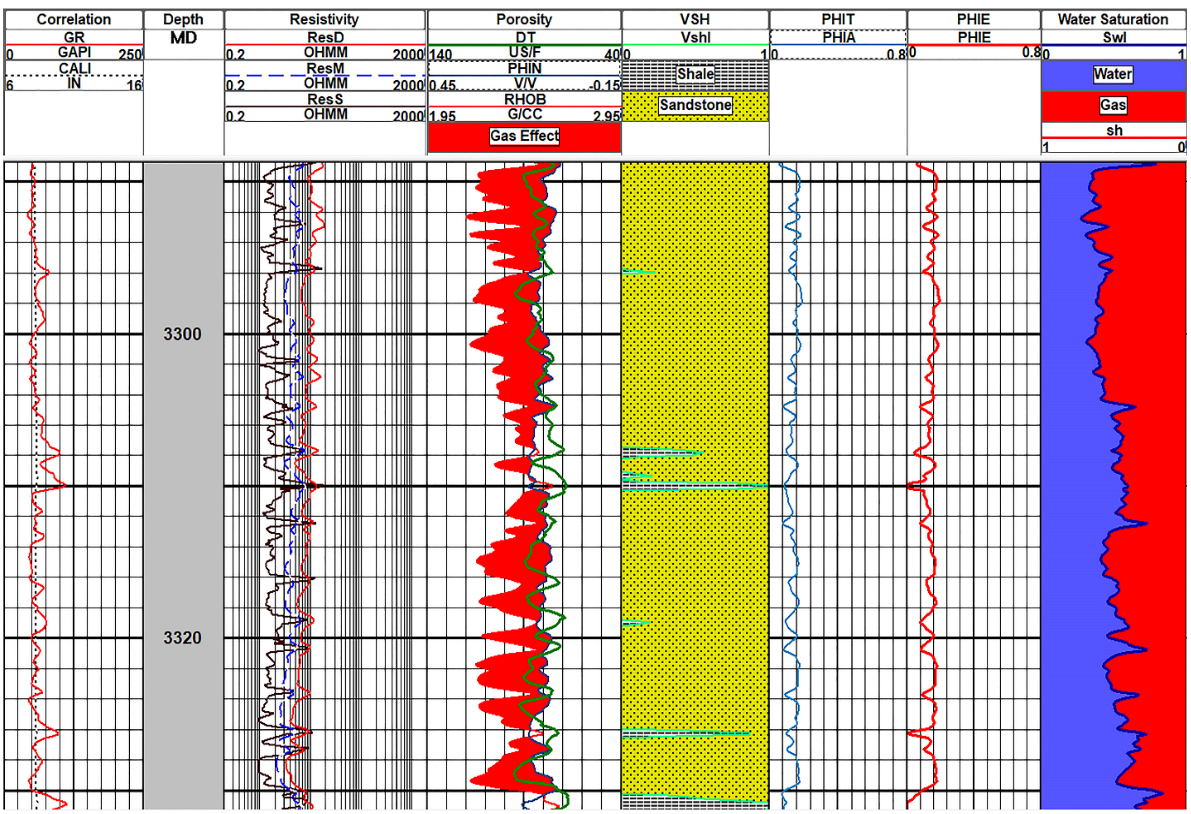

Fig. 4. Petrophysical interpretation of well logs.

3.1. Wavelet Extraction

Wavelet estimated on the seismic database helps deliver true reflectivity series. As a result of the earth's reflectivity convolution with the source wavelet, the seismic trace is obtained. The wavelet extraction procedure includes the statistical estimation of wavelets from the seismic cube. As shown in (Figure 5), the extracted wavelet is obtained by using an operator that gives an initial correlation between real and synthetic data when convoluted with the reflectivity series of well (Jain, 2013). The extraction time window was set from 1600 to 2400 milliseconds with a wavelength of 160 milliseconds.

3.2. Well to Seismic Tie

After wavelet extraction, the next step was to perform well to seismic tie of Lower Goru Formation in all the wells. A synthetic seismogram helps generate well seismic ties and identify events corresponding to reservoir sands (Chukwuemeka, 2021). The logs used for seismic to well tie include Gamma Ray, Sonic and density log. The correlation is done on seismic inline 793, and one zone, "Lower Goru Formation", is marked. In (Figure 6), red traces are actual traces, and the blue traces are synthetic traces having a maximum coefficient of 77%.

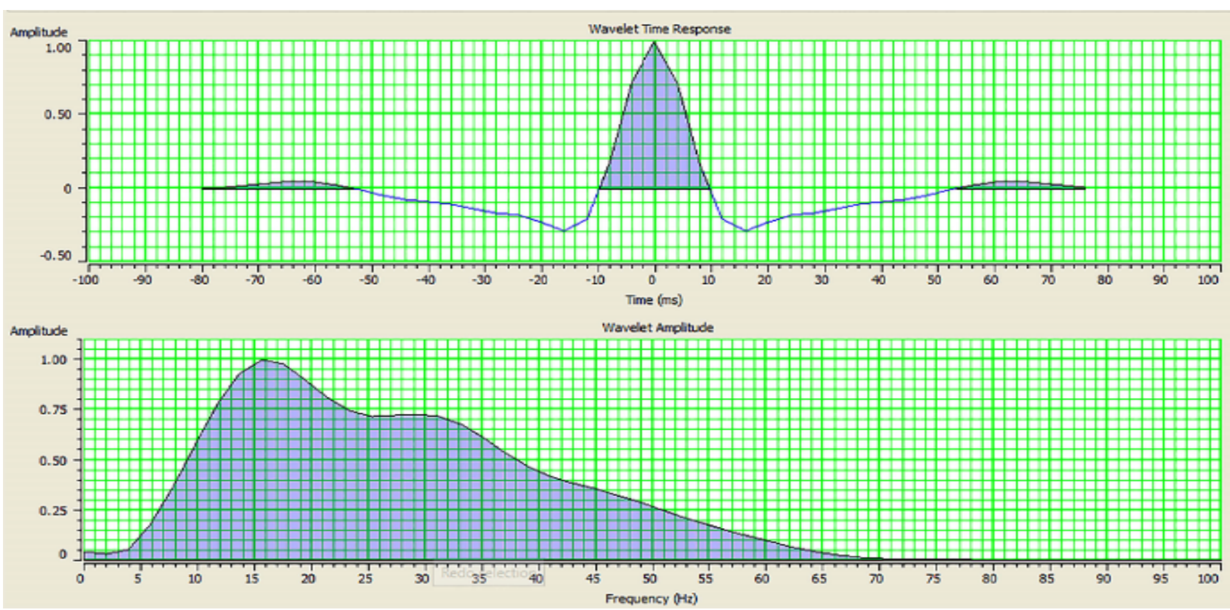

Fig. 5. Extracted Wavelet from seismic cube.

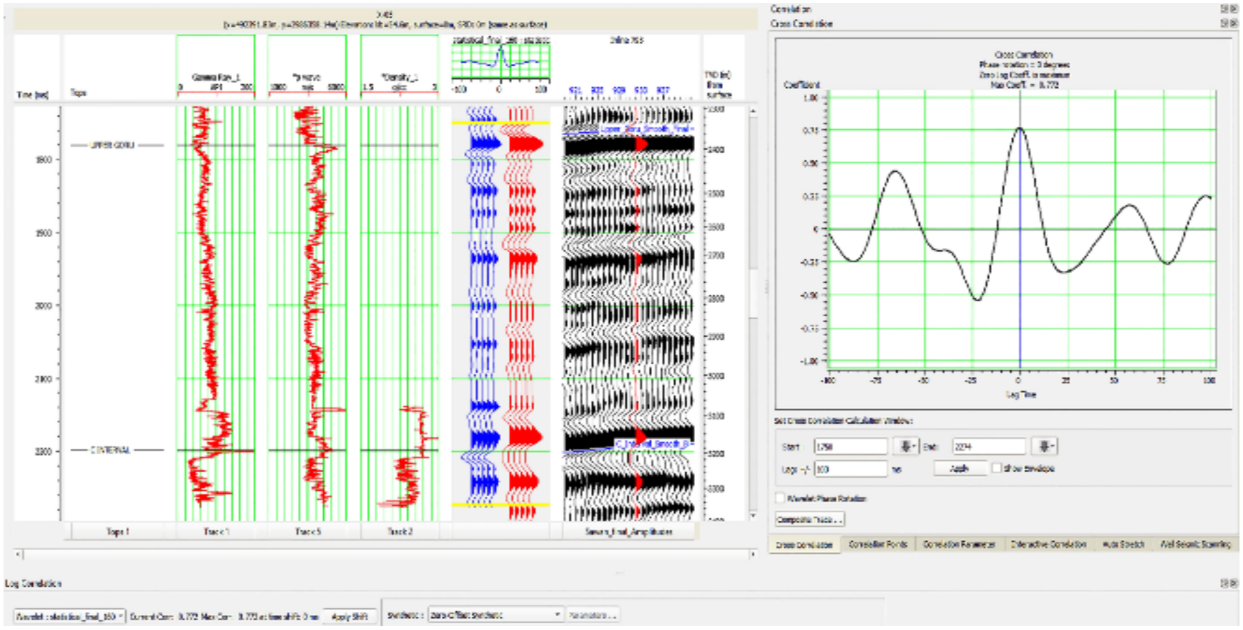

Fig. 6. Well to seismic tie where red curves are indicating actual trace and blue curves are indicating the synthetic trace generated with the help of wavelet extracted from seismic cube.

3.3. Band limited Inversion

Waters invented the Seismic Approximate Impedance Log (SAIL) inversion method in 1978 (Waters, 1978). The help of which velocities and well logs can be stacked for acquiring impedance values from low-frequency data. Ferguson and Margrave proposed a new impedance inversion technique on SAIL dubbed Band limited inversion in the year 1996. The technique utilizes low frequencies data of 2 Hz and 10 Hz (Ferguson & Margrave, 1996). With the help of inversion methodology, the post-stack seismic data was converted into an impedance, density, and P-wave velocity. Defining the relationship between the trace and seismic impedance is the first step of this methodology. As a result, the normal incidence reflection coefficient is defined as

$$r_i = \frac{Z_{i+1} - Z_i}{Z_{i+1} + Z_i} \tag{1}$$

Here, Zi is the seismic impedance of the jth layer, and ri is the seismic reflectivity of jth and (j+1) the interface. By solving the equation for impedance (j+1) the layer, it will become

$$I_{j+1} = I_1 \exp(\gamma \sum_{k=1}^{j} S_k) \tag{2}$$

A robust approach that delivers a smooth and continuous output is Band-limited inversion. In contrast to Band-limited inversion, model-Based inversion gives a blocky result with greater geological information. Both approaches, however, may be beneficial in determining the location of hydrocarbon resources.

3.4.Model Based inversion

This inversion is done by inverting a seismic trace restricted by an a priori model to increase resolution. A basic initial acoustic impedance model is convolved with the wavelet in a model-based inversion to create a synthetic response compared with the real trace. Iteratively altering the acoustic impedance model until the discrepancy between the inverted and seismic traces is decreased to a threshold value. As a solution, a model with a minor difference is approved. Model-Based inversion can produce excellent findings even with inadequate well and seismic quality.
In model-Based inversions, a generalized linear inversion method is utilized. This method assumes that the interpreters are familiar with the seismic trace and wavelet. Moreover, attempts were made to change the initial guass model until the computed trace matches the real trace to an acceptable degree (Gavotti *et al*., 2013). The model is changed many times until the synthetic, and actual seismic traces show the minimum difference. The basic strategy of the inversion algorithm is to solve the function provided in the equation and quantify any changes in synthetic data from real data (Gavotti *et al*., 2013)

$$J = weight_1 x(S - W * R) + weight_1 x(M - H * R) \tag{3}$$

S is an actual seismic trace, R is RC series, W has extracted wavelet, and H is integration operator.

3.5.Stochastic inversion

Stochastic inversion is a method for predicting reservoir parameters distant from the well, which are critical inputs for reservoir modelling. The method incorporates interdisciplinary data from various sources and enables the creation of several earth-model realizations that consider both seismic and good log data. It is also helpful in highlighting the uncertainties in quantifiable data. The earth-model estimate is restricted by seismic, regional geostatistics, and acoustic impedance data from logs to fit the area's known geological trends (Nanda, 2016).

It's a statistical method that generates several different model realizations that meet the observed data. It utilizes the following convolution model:

$$S(t) = R(t) * W(t) + N(t), (1) \tag{4}$$

Where S(t) is the symbol for seismic trace, R(t) represents the reflectivity, W(t) is the wavelet and N(t) represent the random noise.

4. Geo-statistical methods

Geo-statistical methods help predict geophysical parameters from well data and seismic data (Pyrcz *et al*., 2014). A probabilistic Neural Network was utilized to compute the volume of clay and effective porosity volume from seismic data. The input data for training include petrophysical well logs (X-01, X-02, X-04, X-05 and X-06) along with 3D seismic cube and inverted results from Band limited, Model-Based and Stochastic algorithms. Inverted results from all three methods are used to estimate the volume of clay and effective porosity volume.

The objective of using geo-statistical methods is to apply a neural network algorithm for clay volume and effective porosity estimation over the whole 3D seismic volume. The first step in accomplishing the objective is building a relationship between seismic and well data via the training process. When the relationship is successfully established, it will be applied to the whole seismic volume. The analysis window for the volume of clay in the wells (X-01, X-02, X-04, X-05 and X-06) is shown in (Figure 7). The black curve in the log track is the value of the actual volume of clay in wells, whereas the red curve is for the predicted volume of clay. The horizontal yellow lines demarcate the analysis window of the wells' data volume of clay. The training process results using a series of attributes show a 0.9398 (93%) correlation between used wells' actual and predicted porosities (Figure 7). In (Figure 8), the cross plot between the actual volume of clay and the predicted volume of clay for the Stochastic inversion using probabilistic neural networks (PNN).

The analysis window for effective porosities in the wells (X-01, X-02, X-04, X-05 and X-06) is shown in (Figure 9). The curves in the log track (Figure 9) are the porosity values in which the black curve indicates the actual porosity, whereas the red curve indicates predicted porosity. The horizontal yellow lines demarcate the analysis window of wells data effective porosity. The training process results using a series of attributes show a 0.94436 (94%) correlation between the actual and predicted porosities of used wells (Figure 9). Using the probabilistic neural networks (PNN) approach, the cross plots between actual porosity and predicted porosity for the Stochastic inversion were plotted (Figure 10). In the cross plot, the predicted porosity is on Y-axis, and the Actual porosity is on X-axis. On the right side, a colour bar is present, and it shows different wells.

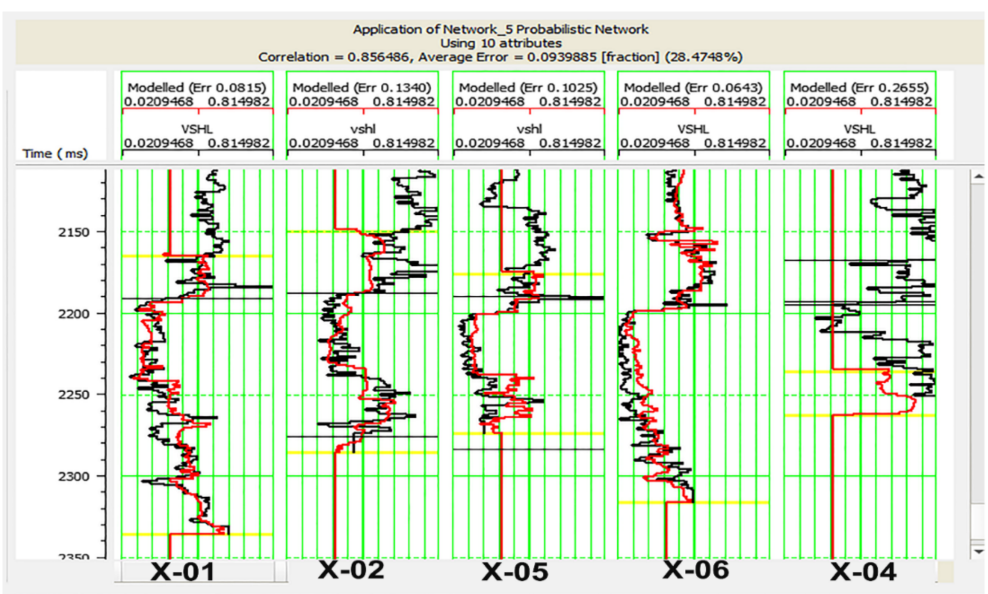

Fig. 7. Analysis of Actual volume of clay (black curve) and predicted volume of clay (red curve) along with the analysis window demarcated above and below by horizontal yellow lines.

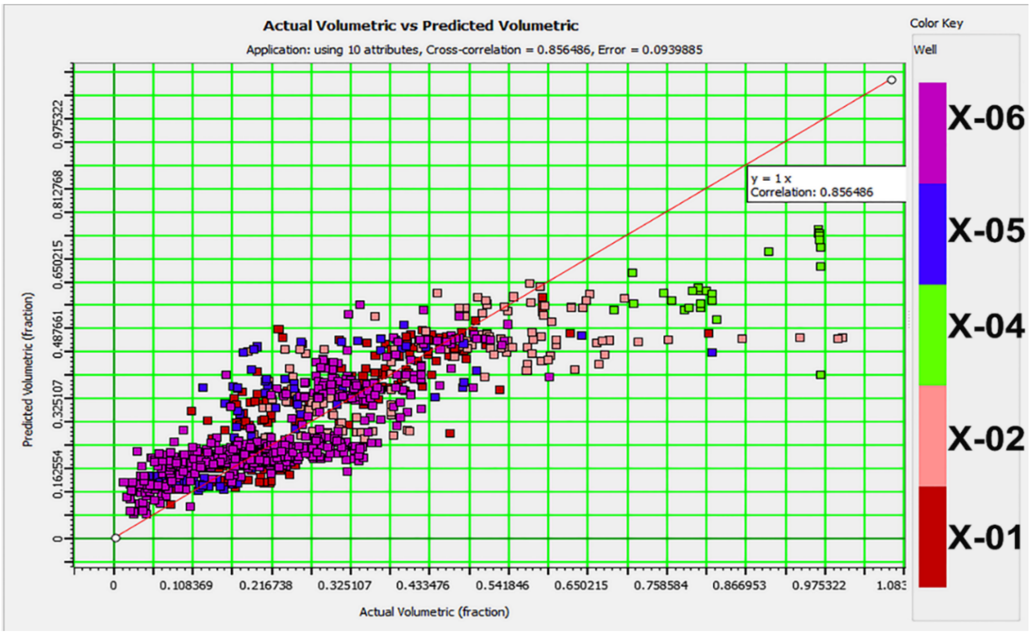

Fig. 8. The cross plot between the actual volume of clay and predicted volume of clay of wells (X-01, X-02, X-04, X-05 and X-06).

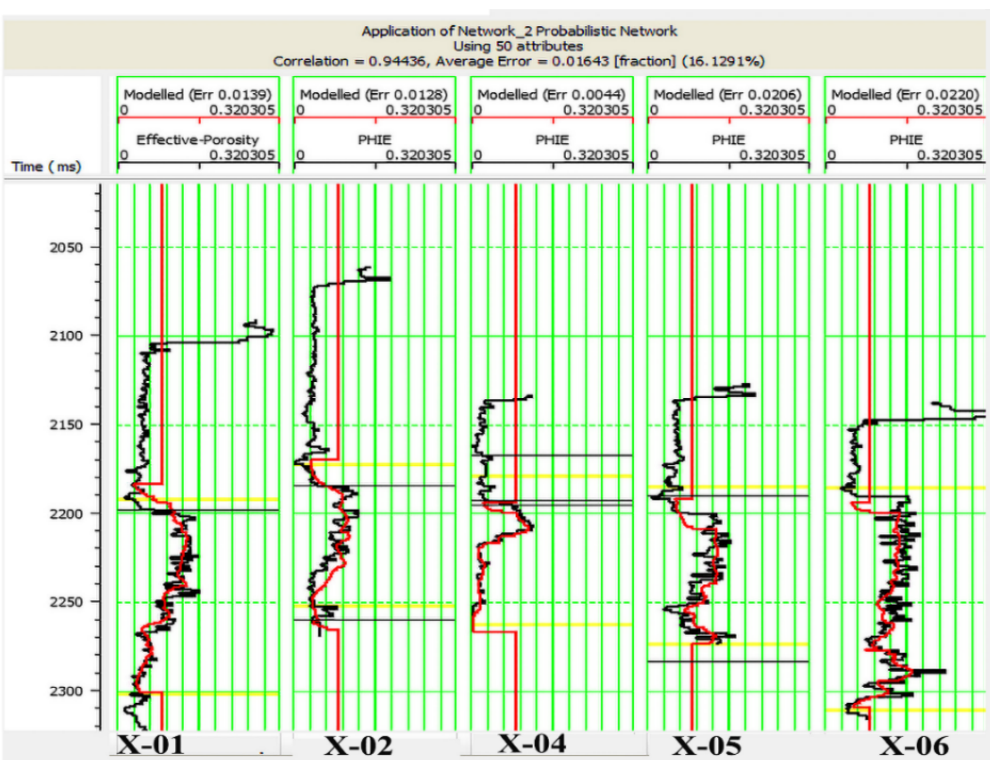

Fig. 9. Analysis of Actual porosity represented by black curve and predicted porosity by red curve along with the analysis window demarcated above and below by horizontal yellow lines.

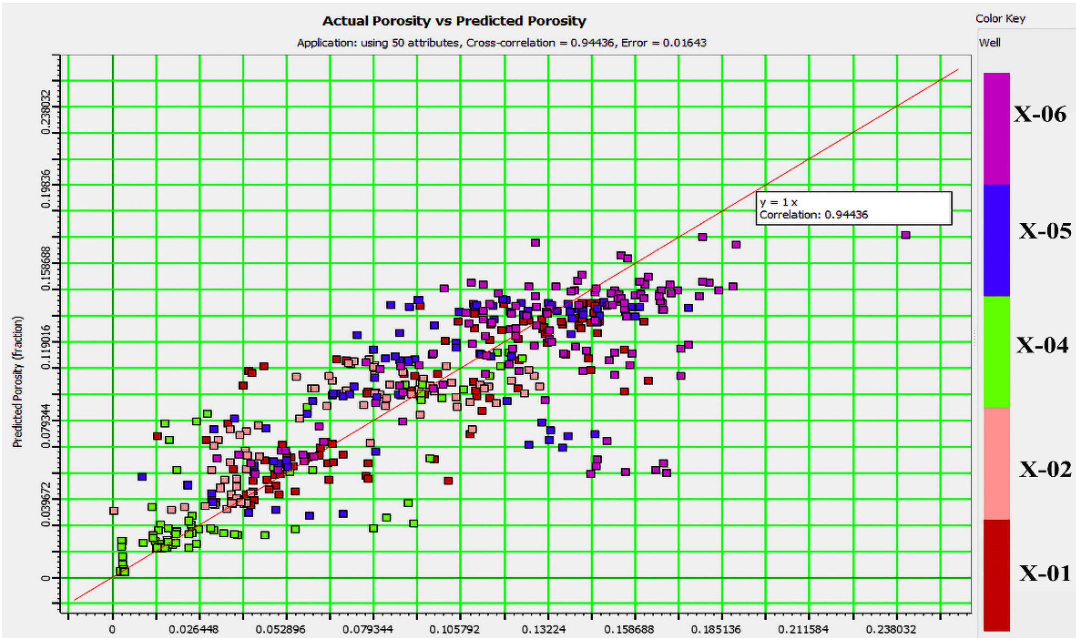

Fig. 10. The cross plot between actual and predicted porosity of wells (X-01, X-02, X-04, X-05 and X-06).

5. Results and Discussion

The study aimed to improve the reservoir characterization of the C-interval sand of the Lower Goru Formation by using different sophisticated inversion techniques (Band limited, Model-Based inversion, and Stochastic inversion) and comparatively analyzed their results. For this purpose, integrating datasets, including seismic and well logs, was utilized to link geological and geophysical information. These inversion techniques successfully delineated isolated sand bodies sandwiched between high impedance (10000-12000 m/s g/cc) shale packages. In addition, Impedance values ranging from 7000-to 10000 m/s g/cc are assigned to the gas-bearing sands and illustrate the potential of the study area (Ibrahim, 2007). These alternative sand-shale facies (clarified by their impedances) are deposited under a deltaic environment followed by forced regression and transgression. Stochastic inversion provided a better result than Band limited inversion and Model-Based inversion (Figures 11a and b). It resolved possible potential sand facies effectively with an improved resolution and provided the best realistic model of subsurface geology (Figure 11c). Stochastic inversion separated the North-eastern part of the study area dominated by clean sand bodies indicating the proximal shore face deposits. In contrast, shale content increases on the Southwestern side, signifying the distal part.

Furthermore, inversion results are trained by the probabilistic neural network algorithm for petrophysical properties estimation i.e., Volume of clay and effective porosities. These petrophysical attributes characterizes the reservoir quality and minimize the exploration risk of targeted potential Lower Goru sands (Khan *et al.*, 2021; Khan *et al.*, 2022). Stratigraphic slices of

Volume of clay by taking average values within C-interval sand of the Lower Goru Formation are generated for all PNN derived results (Band limited, Model-Based and Stochastic) (Figures 12a, b and c). In comparison, the stochastic map provided improved facies distribution that is aligned with geological setting. The map highlighted three different facies such as clean sands (10-30%) passing through X-01, X-05 and X-06 wells, shaly sand (30-35%) encounter at well X-03 while shale facies (>45%) at well location X-04 (Figure 12c). All these facies are verified by the petrophysical evaluation of each well.

Similarly, effective porosities map is generated with average values of C-interval sand of the Lower Goru Formation extracted by the training of inversion results through PNN algorithm i.e., Band limited, Model-Based and Stochastic (Figures 13a, b and c). Likewise, Stochastic inversion resolved the heterogeneous porosities of reservoir sands more efficiently. The map shows high effective positives of 10-12% in the clean sand facies, 8-10% in the shaly sand facies and minimum effective porosities of about 0-1% for the shales.

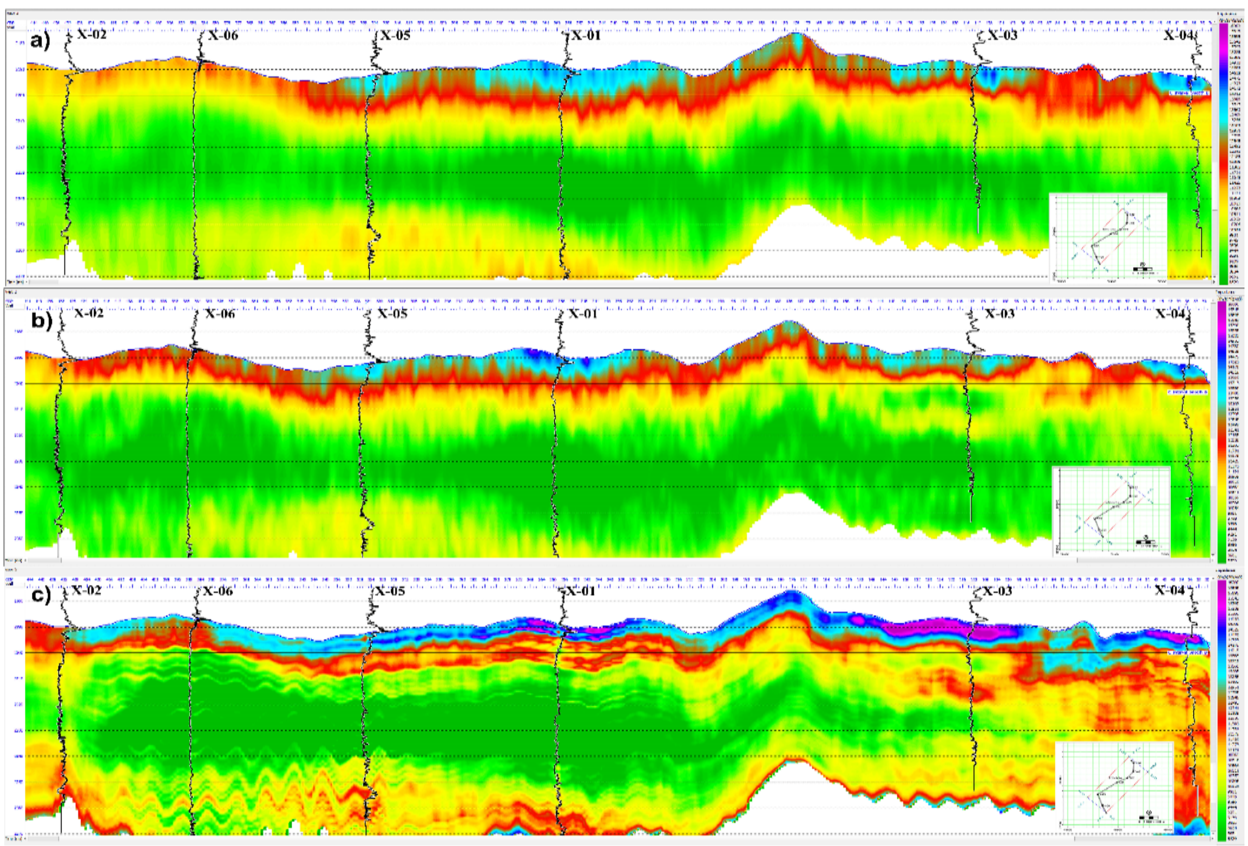

Fig. 11. P impedance for (a) Bandlimited Inversion (b) Model-Based inversion (c) Stochastic inversion.

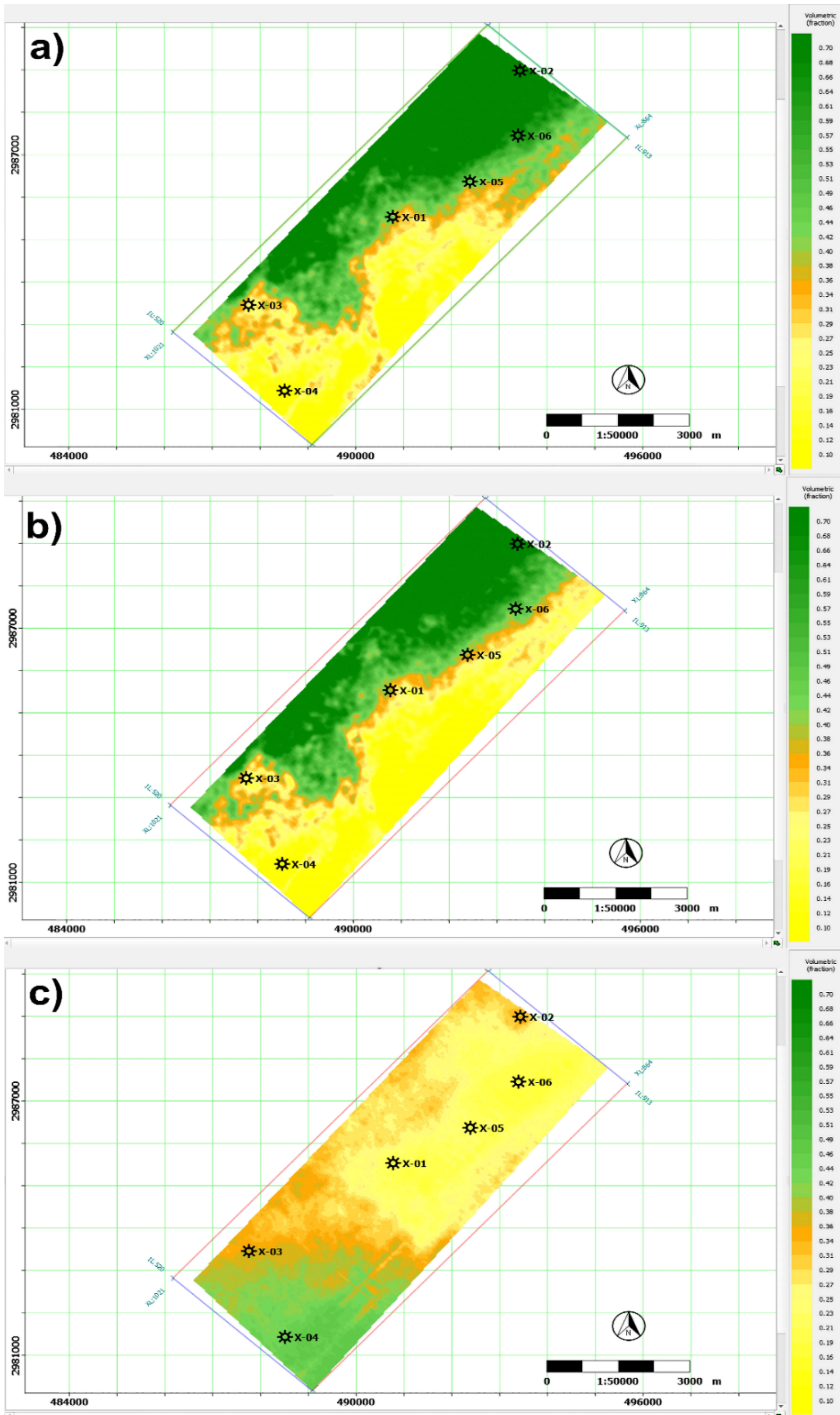

Fig. 12. Estimation of Volume of clay (Vclay) of C-interval sands of Lower Goru Formation using post-stack inversion techniques including (a) Band limited Inversion (b) Model-Based inversion (c) Stochastic inversion.

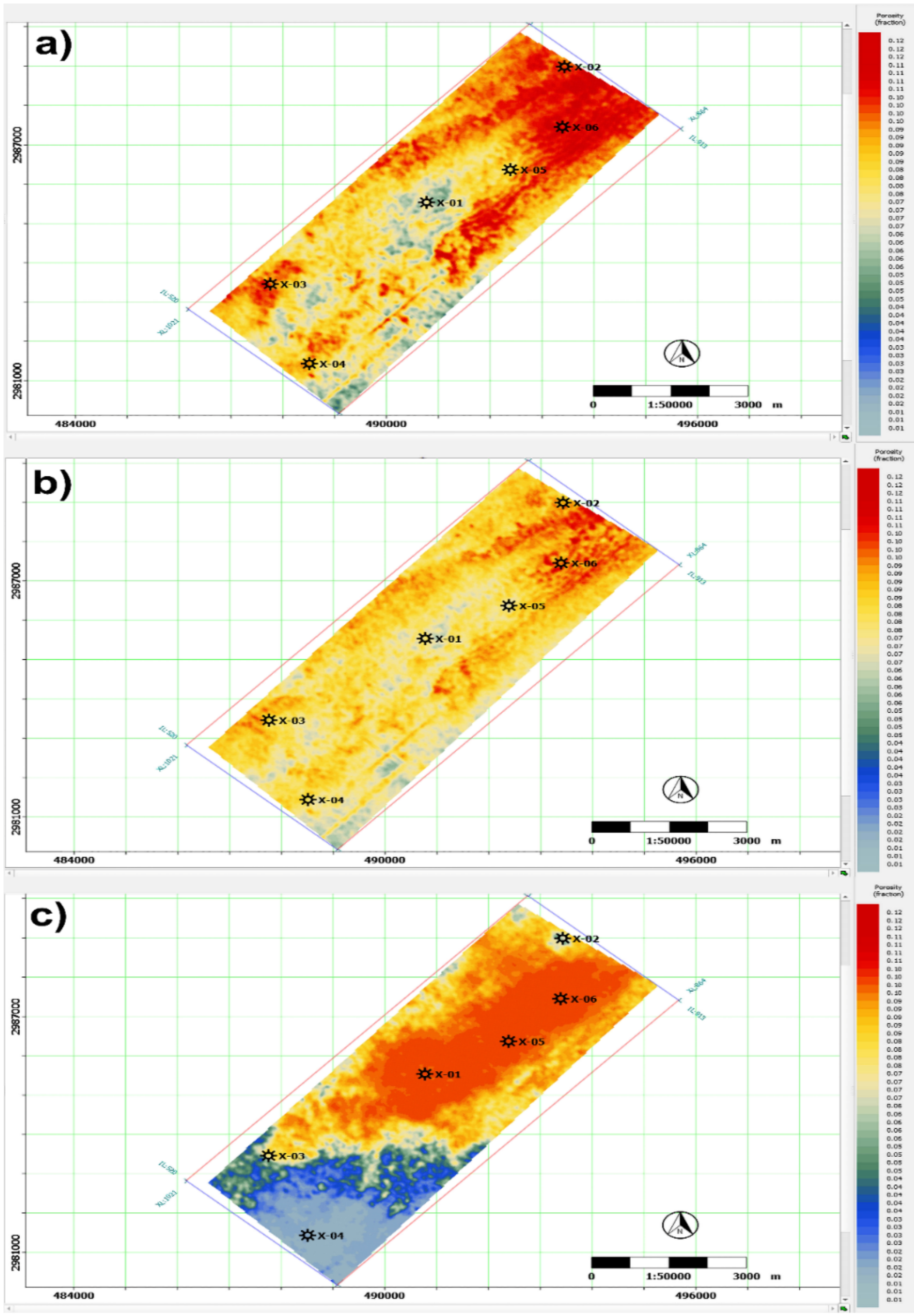

Fig. 13. Effective porosity estimation of C-interval sands of Lower Goru Formation using post-stack inversion techniques including (a) Band limited Inversion (b) Model-Based inversion (c) Stochastic inversion.

6. Conclusion

The comparative analysis among three seismic inversion techniques (Band limited inversion, Model-Based inversion and Stochastic inversion) successfully characterizes the reservoir facies of C-interval sands of the Lower Goru Formation. The highly resolved Stochastic inversion best differentiates between producing and non-producing reservoir facies. The PNN trained stochastic attributes for petrophysical properties to illuminate potential sands with low P-impedances, high effective porosity, and low clay volumetric. The results are in accordance with interpreted wells (X-04 was kept blind) and geological settings. Hence Stochastic inversion overcomes many problems effectively, such as assessing heterogeneity and quality of the reservoir. The north-eastern wells (X-01, X-05, X-06 and X-02) have clean sand facies with a low volume of clay and high effective porosity delineating the main producing facies. Whereas, moving towards the southwestern side, the wells (X-03 and X-04) have finer sediments, greater shale volume, and low effective porosity resulting in poor reservoir quality.

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