Phi: Jurnal Pendidikan Fisika dan Terapan
Vol. 12, No. 2 (2026) 356-369
ISSN: 2460-4348, e-ISSN: 2549-7162
https://jurnal.ar-raniry.ac.id/index.php/jurnalphi/index

Article Type: *original research*

Characterization of the Menggala Formation Sandstone Reservoir Using Multi-Attribute Seismic in the "X" Field, Central Sumatra Basin

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ARTICLE INFO

Article History:
Received: 16 April 2026
Revised: 24 May 2026
Accepted: 22 July 2026
Published: 26 July 2026

Keywords:
Multi-attribute; Seismic 2D/3D; Reservoir characterization

ABSTRACT

Field X in the Central Sumatra Basin presents unique characteristics due to suboptimal data quality for seismic inversion analysis. However, a comprehensive reservoir characterization is still required. Therefore, alternative strategies are needed to optimize the available data, one of which is multi-attribute seismic analysis. This study aims to characterize the reservoir in the Menggala Formation, Central Sumatra Basin, using multi-attribute seismic analysis. The petrophysical parameters used include density porosity (DPHI), water saturation (Sw), and shale volume (Vsh) as primary indicators for assessing reservoir quality. The dataset consists of post-stack 3D seismic data and well log data from four calibration wells, including gamma ray, density, neutron, and resistivity logs. The research workflow began with petrophysical analysis to derive DPHI, Sw, and Vsh values from the well log data, followed by seismic attribute extraction within the target reservoir intervals. Multi-attribute linear regression was then applied to establish a quantitative relationship between seismic attributes and well log data, enabling the lateral prediction of petrophysical parameter distributions across the study area. Model validation was conducted by comparing the predicted values against well log data, yielding correlation coefficients of r= 0.63 (Vsh), r= 0.85 (DPHI), indicating sufficiently reliable and acceptable prediction results. Based on the modeled property distributions, potential reservoir zones are characterized by low Vsh, high DPHI, reflecting the presence of clean sandstone with good hydrocarbon potential. These findings serve as a valuable reference for identifying prospect zones and supporting future development planning within the study area.

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1. INTRODUCTION

The Central Sumatra Basin is one of the most important hydrocarbon basins in Indonesia, playing a major role in national oil and gas production. Tectonically, this basin developed as a back-arc basin formed by the subduction of the Indo-Australian Plate beneath the Eurasian Plate in the southwestern part of Sundaland (Widhiyatmoko et al., 2024). The complexity of the tectonic and stratigraphic evolution in this basin has resulted in a well-developed petroleum system,

characterized by the presence of adequate source rocks, reservoirs, and cap rocks (Dwi Putri et al., 2023).

The evaluation of hydrocarbon reservoir quality is highly dependent on rock petrophysical parameters, such as shale volume (Vshale), water saturation (Sw), and density-porosity (DPHI). These parameters are generally derived from well data through petrophysical log analysis (Somasundaram et al., 2017). Previous studies in the Central Sumatra Basin have predominantly relied on seismic inversion approaches to characterize petrophysical parameters (Hampson et al., 2001; Russell et al., 1997). However, these approaches assume a robust correlation between acoustic impedance and petrophysical properties, which is not always present in every field. In this study, Field X in the Central Sumatra Basin represents a unique case study, as it faces limitations in well data quality, which generally do not show good correlation among the parameters. For example, the relationship between acoustic impedance values and porosity, which generally exhibits an inverse trend in clastic reservoir, does not show any discernible trend in the well data (scatter) (Wibowo et al., 2020). This condition results in acoustic impedance analysis from seismic inversion being suboptimal for characterizing petrophysical parameters such as porosity, Vshale, and water saturation (Sw). Therefore, this paper will employ an alternative method using multi-attribute seismic data to characterize the sandstone reservoir of the Menggala Formation, Field X, in the Central Sumatra Basin.

A multi-attribute seismic method was applied to predict petrophysical parameters such as Vshale and porosity. The results of this study are expected to provide an overview of the lateral and vertical distribution of petrophysical parameters, as well as serve as a reference for assessing the quality of hydrocarbon reservoirs in the study area (Ardinda & Riyanto, 2020). To address these limitations, integration with seismic data covering a wide area (post-stack 3D) is required (Lestari et al., 2023). One widely used approach is the multi-attribute seismic method to estimate these petrophysical parameters.

Seismic multi-attribute analysis is a method that applies a geostatistical approach by utilizing more than one seismic attribute to estimate and predict the physical properties of subsurface rocks (Hampson et al., 2001; Russell et al., 1997). Multi-attribute linear regression is performed to obtain an operator capable of predicting well log values based on seismic data around the well location (Aziz & Setiawan, 2017; Hampson et al., 2001). The validation process is used as a parameter to assess the level of accuracy and determine the most appropriate number of attributes to use in the prediction (Huda et al., 2013). The novelty of this study lies in the application of multi-attribute seismic analysis in a field where conventional seismic inversion is ineffective due to the absence of a clear acoustic impedance–porosity relationship, a condition that has not been specifically addressed in prior studies within the Central Sumatra Basin. Based on the above description, this study aims to map porosity and Vshale using multi-attribute seismic techniques, while Sw interpretation is restricted to DZ-4 to improve the effectiveness of oil and gas reservoir exploration and evaluation activities, particularly in new work areas that still have untapped potential in the Central Sumatra Basin.

2. METHODS

2.1 Geology of the Study Area

The study area is located in the Central Sumatra Basin, which is geographically bordered by the North Sumatra Basin to the north and the South Sumatra Basin to the south (Figure 1). Regionally, this basin developed as a back-arc basin formed by the subduction of the Indo-Australian Plate beneath the Eurasian Plate (Bachri, 2006). This tectonic activity plays a significant role in the formation of geological structures and sedimentary deposition processes in the Central Sumatra Basin (Dwi Putri et al., 2023).

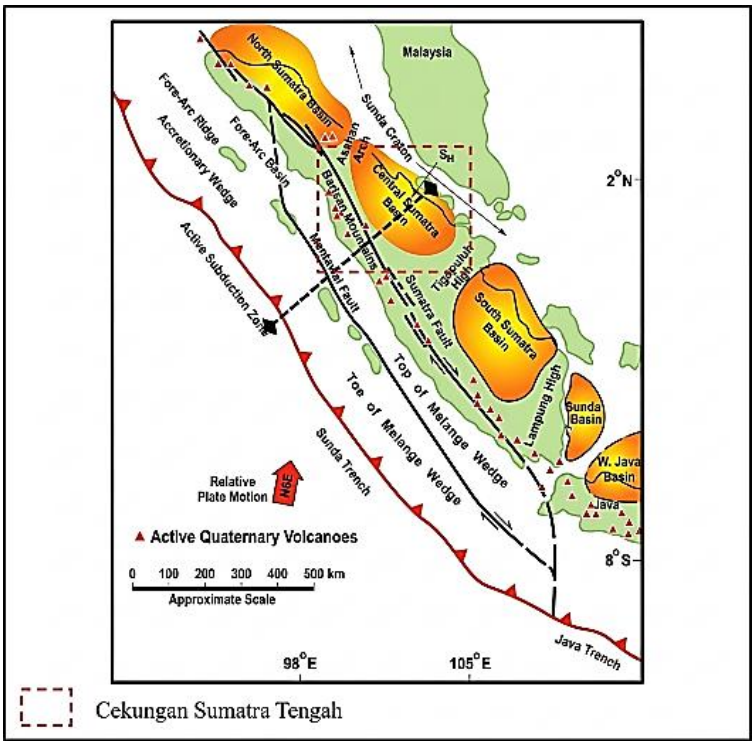


Figure 1. Physiographic Map of Basins in Sumatra (Dwi Putri et al., 2023)

This study covers the Lower Menggala Formation through the Pematang Formation, which serve as source rocks and reservoirs (Figure 2). These formations possess excellent lithology, such as carbonate shale and sandstone. Therefore, the objective of this study is to determine whether the area is indeed suitable as a reservoir, in addition to focusing on the lithology of the Pematang and Menggala formations (Meninta et al., 2015).

In Figure 2, the Menggala Formation is marked by a red box and consists stratigraphically of alternating fine- to coarse-grained sandstones with some limestone dating to the Early Miocene, specifically around ± 24–21 million years ago.

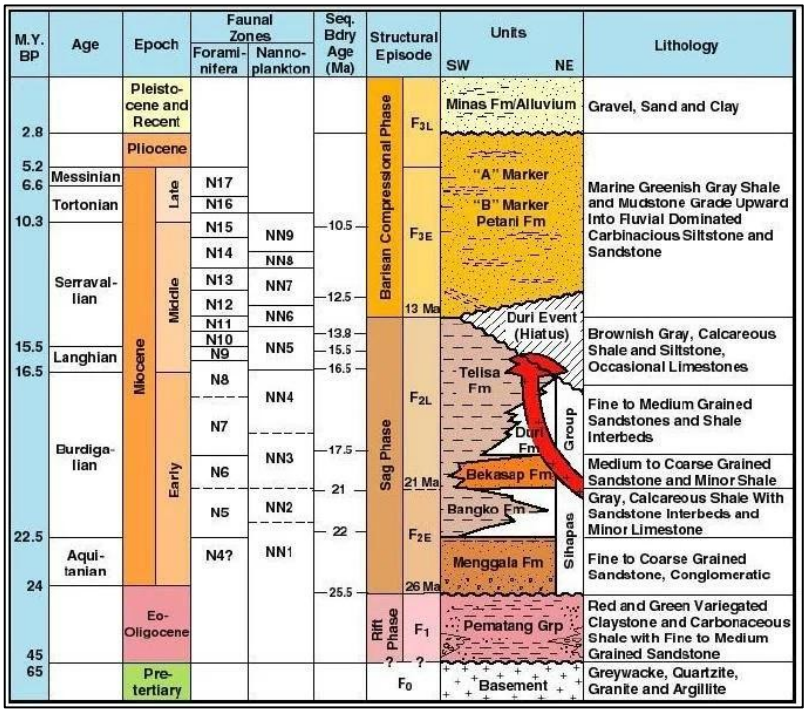


Figure 2. Regional stratigraphy of the Central Sumatra Basin (Meninta et al., 2015)

2.2 Methods

3D post-stack seismic data is the result of processing three-dimensional seismic data that has undergone stacking and migration, producing subsurface images with high structural resolution (inline and crossline). The study is limited to inline 5248–5538 and crossline 5466–5532. There are four well data sets, as shown in Table 1.

Table 1. Well Data Availability

Log Type	Well			
	DZ-1	DZ-2	DZ-3	DZ-4
Caliper	x	v	v	v
Gamma Ray	v	v	v	v
NPHI	v	x	x	v
RHOB	v	v	v	v
Resistivity	x	x	x	v
Checkshoot	v	v	v	v
Vshale	x	x	x	x
Water Saturation	x	x	x	v
Porosity	x	x	x	x
Inline	5385	5538	5428	5248
Xline	5466	5471	5357	5532

This study employs quantitative seismic interpretation techniques such as rock physics, post-stack seismic inversion, and seismic attributes. In rock physics, log processing was performed to generate porosity logs, shale volume logs, and water saturation logs (Burchartz et al., 2026):

1. Porosity Log
   Porosity logs are an important tool in the oil and gas industry for evaluating the potential of rocks as reservoirs, measuring the volume of voids in the rock that can be filled with fluid (Koesoemadinata, 1980). This study produced porosity logs using density logs (ρ_{obs}), where the fluid density (ρ_f) is 1.09 g/cc for standard brine, and the matrix density (ρ_{ma}) is 2.65 g/cc for standard sandstone. The following formula is used to determine porosity using density:

$$\text{Porosity Calculation: } \emptyset = \frac{\rho_{ma} - \rho_{obs}}{\rho_{ma} - \rho_f} \quad (1)$$

2. Shale Volume Log
   To generate a shale volume log, a gamma ray (GR) log is required; the method used to determine shale volume is the non-linear Steiber method. This method is used because it assumes that the GR response to shale is not always linear, due to the effects of rock age, compaction, and radioactive mineral content (Bagaskara et al., 2023). The following is the formula for determining shale volume using GR with the Steiber method:

$$\text{Vshale} = \frac{0.5 \times \text{GRindex}}{1.5 - \text{GRindex}} \quad (2)$$

3. Water Saturation Log
   Water saturation is the ratio of the pore volume filled with water to the total pore volume (Purba & Mulyatno, 2020). Water saturation (Sw) was calculated only for well DZ-4 because it is the only well equipped with resistivity log data. The other three wells (DZ-1, DZ-2, and DZ-3) do not have resistivity logs. Therefore, Sw could not be computed using Archie's equation for those wells. Consequently, Sw interpretation in this study is restricted to well DZ-4 and is not used as a training target for multi-attribute seismic regression.

The water saturation log at well DZ-4 is derived from the Archie equation, where the cementation factor (a) is 1, the cementation exponent (m) is 1.8, the formation water resistivity (Rw) is 0.04 Ω·m, and the saturation exponent (n) is 2. These parameter values are default settings

provided by the HRS (Hampson-Russell Software) application, which applies industry-standard default values for clastic reservoir analysis. The following is the formula for water saturation using Archie's equation:

$$\text{Archie's Equation: } Sw^n = \frac{a}{\emptyset^m} \times \frac{Rw}{Rt} \quad (3)$$

After log processing, the next step involves seismic wavelet extraction and model-based inversion. In this study, a Ricker wavelet was selected for the inversion process. The Ricker wavelet was chosen over well-based and statistical wavelets because both alternatives yielded poor wavelet-seismic tie (WST) correlation values in the study area, indicating that those wavelet types were not representative of the seismic data characteristics at Field X.

The model-based inversion was performed to derive the acoustic impedance (AI) distribution and construct an optimal subsurface model (Rifai et al., 2019). It is important to note that the inversion was applied solely for AI prediction. Initial attempts to derive porosity, Vshale, and water saturation directly from the inversion yielded poor regression results, indicating that the acoustic impedance data alone were insufficient to reliably predict these petrophysical parameters in this field (Adrian et al., 2018). This condition is consistent with the scatter observed in the acoustic impedance porosity crossplot, which shows no clear inversely proportional trend, as noted in the introduction (Figure 3).

To evaluate the feasibility of using acoustic impedance inversion for porosity prediction, a cross-plot analysis between inverted acoustic impedance (AI) and density-derived porosity (DPHI) was performed at well locations within the Menggala Formation interval, with a correlation coefficient (r) calculated to quantitatively measure the strength of the relationship between the two, which in clastic reservoirs generally shows an inverse trend (Wardhani et al., 2025). If the resulting correlation proves to be poor, it would indicate that AI inversion alone is insufficient for good porosity prediction, necessitating alternative approaches such as multi-attribute seismic regression to better capture the complexity of petrophysical relationships within the study interval.

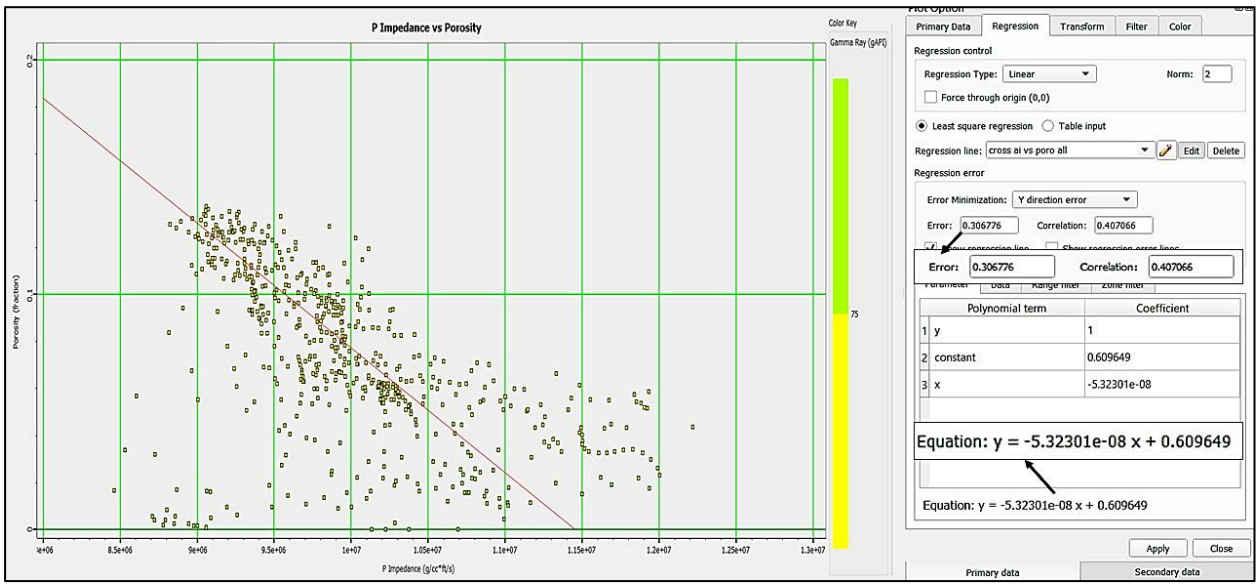


Figure 3. Crossplot AI vs Porositas (DPHI) for well DZ-1, DZ-2, DZ-3, DZ-4

To address this limitation, multi-attribute seismic analysis was adopted as an alternative approach for predicting the lateral distribution of porosity (DPHI), shale volume (Vshale). Water saturation (Sw) interpretation was restricted to well DZ-4 and was not included in the multi-attribute prediction workflow. Multi-attribute linear regression was performed to establish a statistical relationship between multiple seismic attributes and the well log data, generating volumetric predictions of each petrophysical parameter across the study area. These volumes are generated to assess reservoir characterization and the distribution of porosity and shale volume in the target area,

while Sw interpretation is limited to well DZ-4 (Retnowati & Yanto, 2018). All processing and analysis were conducted using the HRS (Hampson-Russell Software) platform.

3. RESULT AND DISCUSSION

3.1 Porosity, Vshale, and Water Saturation Logs

The target zone shown in Figure 4 displays Vshale logs from four wells (DZ-1 to DZ-4). The target zone in the Menggala Formation is characterized by variations in Vshale value. The average Vshale value and reservoir thickness for each well are summarized in Table 2. Overall, this Vshale distribution indicates lateral reservoir heterogeneity, which may be influenced by changes in sedimentary facies from clean sandstone to clay-rich sandstone. The average Vshale value from the four wells is 0.166 (0–1 fraction), indicating that the target zone is generally still dominated by relatively clean reservoir rocks (clean to slightly shaly sandstone) with an average reservoir thickness of 75.47 m, indicating potentially good reservoir quality.

In general, Vshale values in the target zone tend to be low to moderate, indicating a dominance of sandstone with shale interbeds present only in certain intervals (S. A. Putri et al., 2025). Well DZ-1 exhibits a relatively cleaner interval with low and stable Vshale, while wells DZ-2 and DZ-3 show a fluctuating pattern characteristic of interbedded sand-shale. In DZ-4, Vshale values tend to be higher compared to other wells. Additionally, this may indicate an increase in shale content and a decline in reservoir quality in that section.

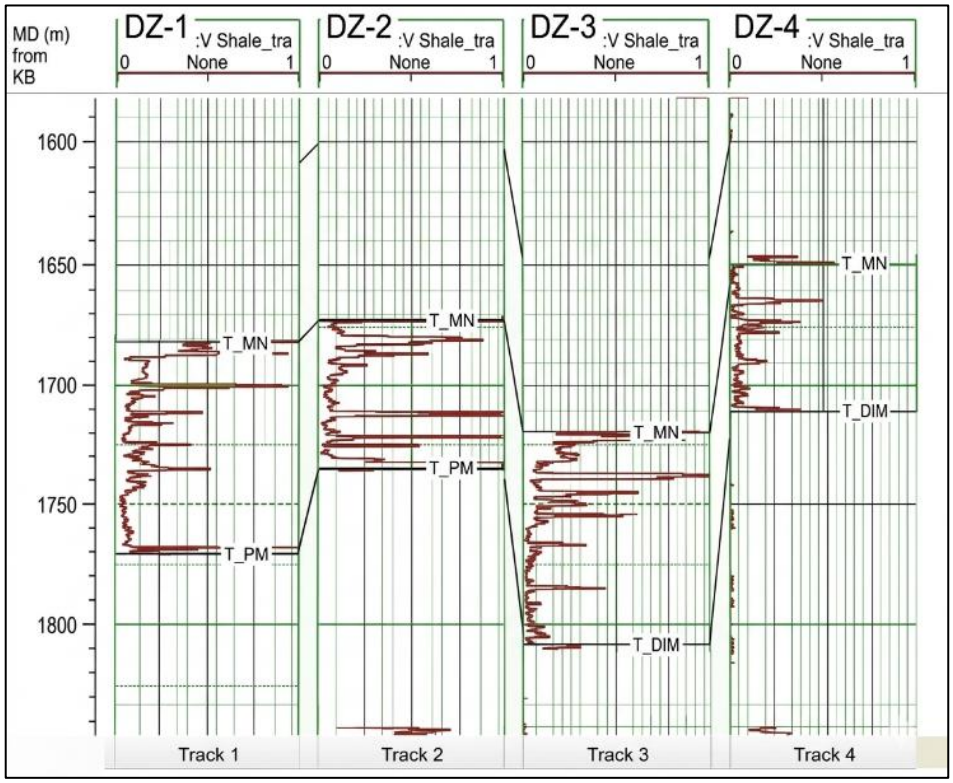


Figure 4. Vshale logs from well data for DZ-1, DZ-2, DZ-3, and DZ-4

Table 2. Value of Volume Shale at Target Zones

Well Name	Value of Vshale	Thickness (m)
DZ-1	0.149	88.85
DZ-2	0.201	62.18
DZ-3	0.243	89
DZ-4	0.073	61.88

Based on the DPHI log analysis (Figure 5), the target reservoir intervals in wells DZ-1 through DZ-4 generally exhibit low to moderate porosity values, indicating varying reservoir quality across

the study area. The average porosity and target thickness for each well are summarized in Table 3. Overall, the reservoir intervals show an average porosity of 0.155, suggesting that the Menggala Formation sandstone in Field X has relatively limited pore space for fluid storage. Variations in porosity between wells likely reflect differences in lithology, shale content, depositional facies, and compaction effects, which collectively contribute to reservoir heterogeneity within the target zone (Zahmatkesh et al., 2018).

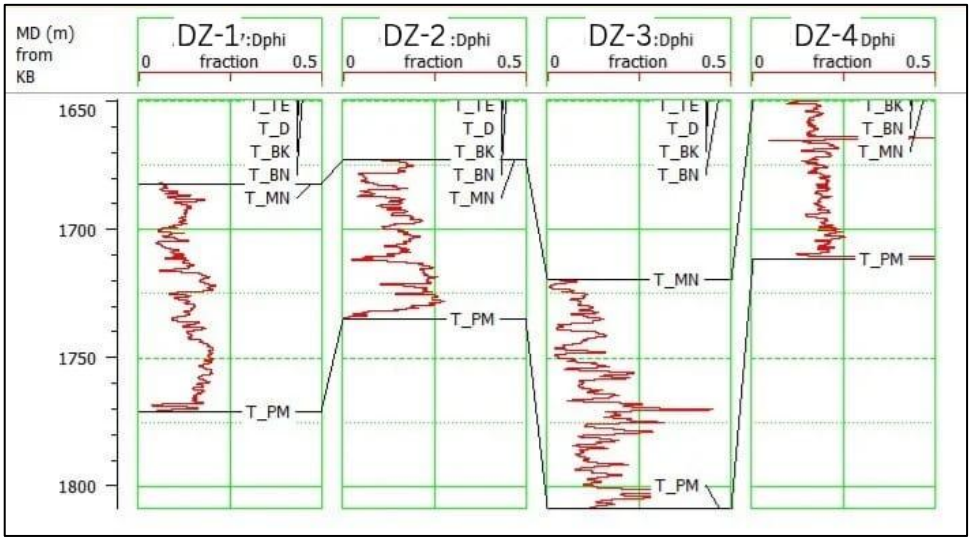


Figure 5. Porosity logs from data for wells DZ-1, DZ-2, DZ-3, and DZ-4

Table 3. Value of Porosity at Target Zones

Well Name	Value of Porosity	Thickness (m)
DZ-1	0.136	88.85
DZ-2	0.154	62.18
DZ-3	0.130	89
DZ-4	0.198	61.88

The water saturation log (Figure 6) is presented only for well DZ-4, as this the only well in the dataset equipped with a resistivity log. Within the target interval of the Menggala Formation, well DZ-4 yields an average Sw value of 0.610 over a net thickness of 61.88 m, reflecting predominantly moderate to high water saturation conditions. This suggests that the interval is largely water-bearing (Rifai et al., 2019). However, several localized zones exhibiting relatively low Sw values may still indicate the potential for hydrocarbon accumulation in discrete portions of the target interval. This water saturation log analysis is supported by a resistivity log showing a relatively high value of 42.029 ohmm at a depth of 1.655 meters, which corresponds to a low water saturation value of 0.136. A low resistivity log reading indicates that the formation contains water. Conversely, a high log reading indicates that the formation contains hydrocarbons (Christoper et al., 2024).

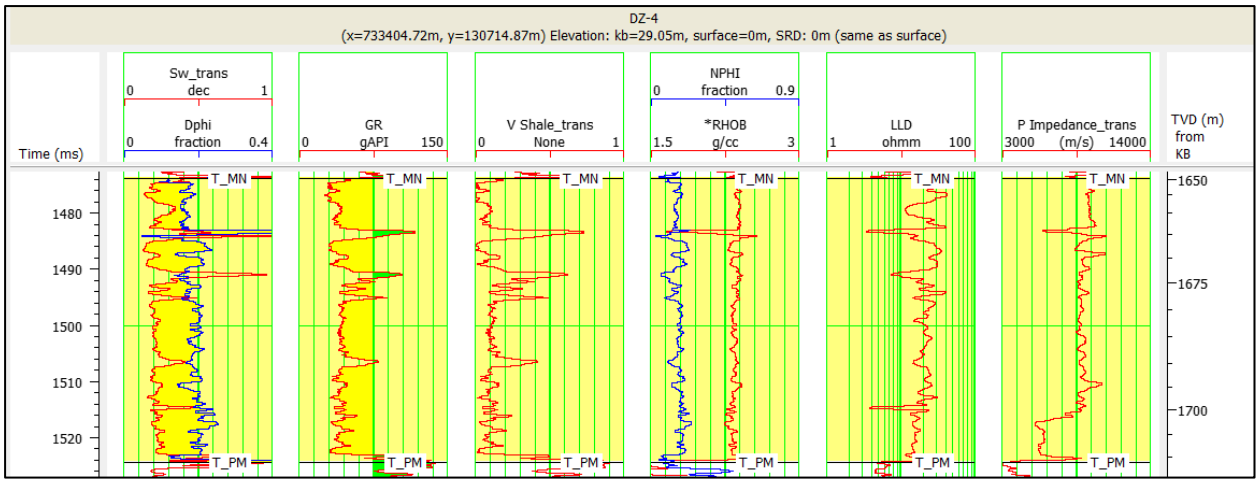


Figure 6. Water Saturation Logs from data for wells DZ-4

3.2 Picking Horizon, Fault, and Time Structure Map

Based on Figure 7, the target zone is delineated by the green and light blue boundary lines, representing the Lower Menggala to Upper Pematang interval. A major fault, marked by a light blue line, has been identified in this area. Additionally, both large and small scale faults have been identified around wells DZ-1 through DZ-4. These faults are believed to act as hydrocarbon traps within the target zone, given that the petroleum trap system in the Central Sumatra Basin is generally controlled by fault structures.

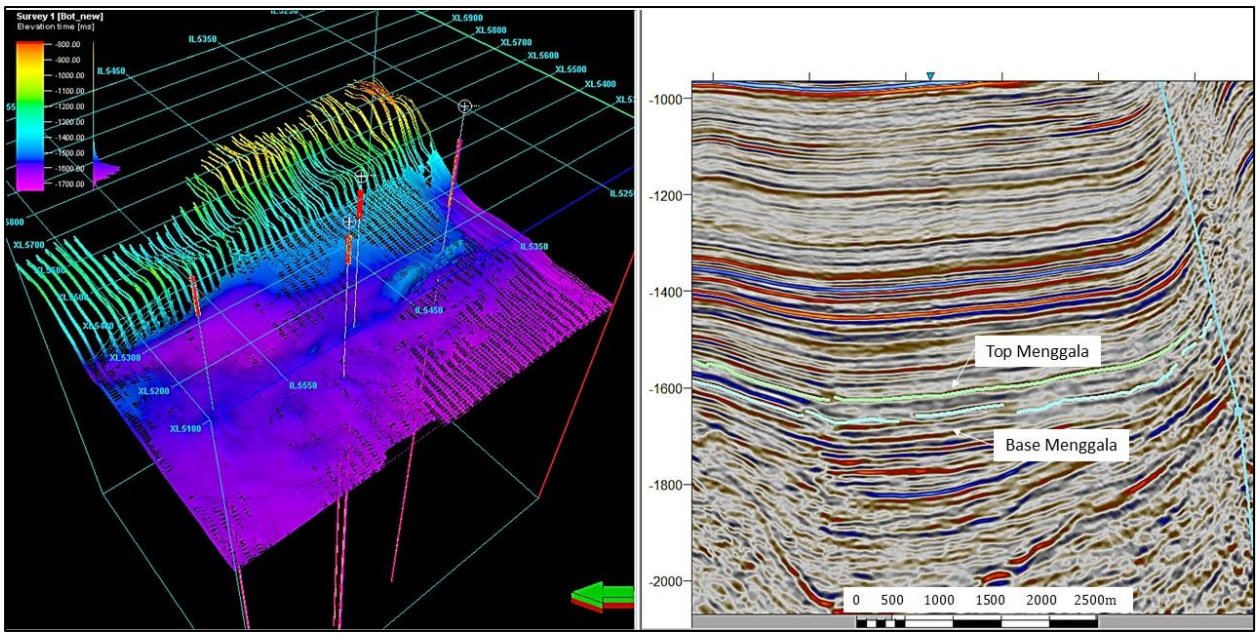


Figure 7. Picking Horizon and Fault on Inline 5447

The time structure map (TSM) in Figure 8 shows high and low-lying areas, as indicated by the color bar. The yellow to orange colored area (elevation time 1500 to 1700 ms) represents a low-lying area, while the purple to green colored area (elevation time 750–1350 ms) indicate high-elevation areas. In this target area, there is also a fault zone near the DZ-4 well (marked with a red line).

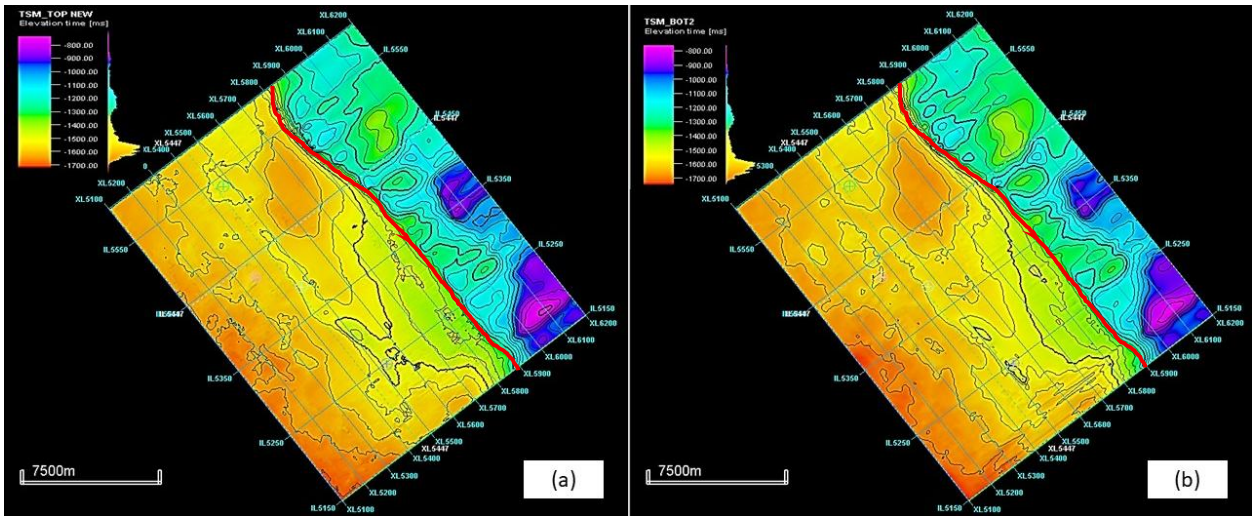


Figure 8. (a) Time Structure Map-Top, (b) Time Structure Map-Base

Figure 9. (a) shows a time structure map overlay of shale volume distribution results, indicating that estimates in the proposed well area (red circle) tend to be lower (0.10–0.40, as seen on the scale bar) compared to the surrounding areas. This may indicate better reservoir quality, as a lower clay fraction can enhance pore effectiveness and permeability. The decrease in Vshale values toward the up-dip indicates clean reservoir deposition on high structures, thereby increasing the likelihood of a hydrocarbon accumulation zone.

The porosity distribution shown in Figure 9(b) indicates that the target well area has relatively high porosity values (0.15–0.25 as seen on the scale bar) and is located in the up-dip part of the structure. Geologically, these conditions support the formation of a hydrocarbon trap because hydrocarbon fluids migrate to higher structural positions and accumulate in reservoirs with good pore quality. Integration of the vshale and porosity distribution maps indicates that the estimated location of the proposed well is in a zone with reservoir characteristics suitable for storing and transporting hydrocarbons, while also allowing for hydrocarbon accumulation (Alsharhan, 2003).

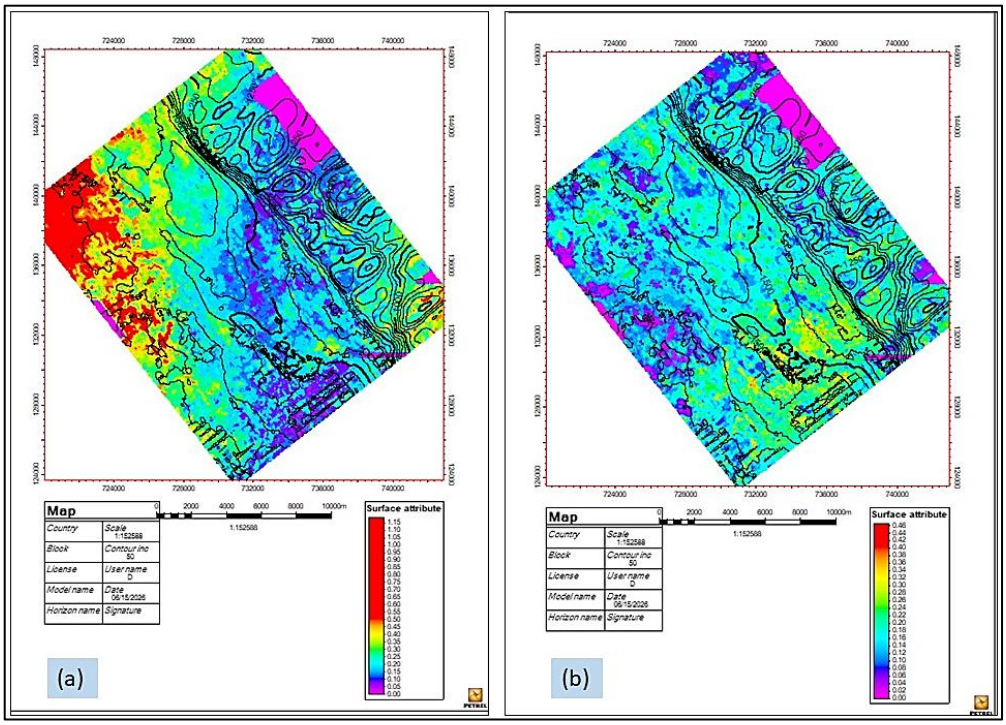


Figure 9. (a) Time Structure Map-Vshale, (b) Time Structure Map-Porosity

3.3 Impedance Acoustic inversion

The inversion results in Figure 10 show that the acoustic impedance values of the reservoir rock in the target area range from 8737 to 11081 [g/cm^3·m/s]. Porous sandstone is highlighted in red within the target formation, where the AI values are relatively lower. The acoustic impedance (AI) distribution map was obtained by extracting the AI volume from the inversion results; the thickness in this zone has a minimum of 61.88 m and a maximum of 89 m.

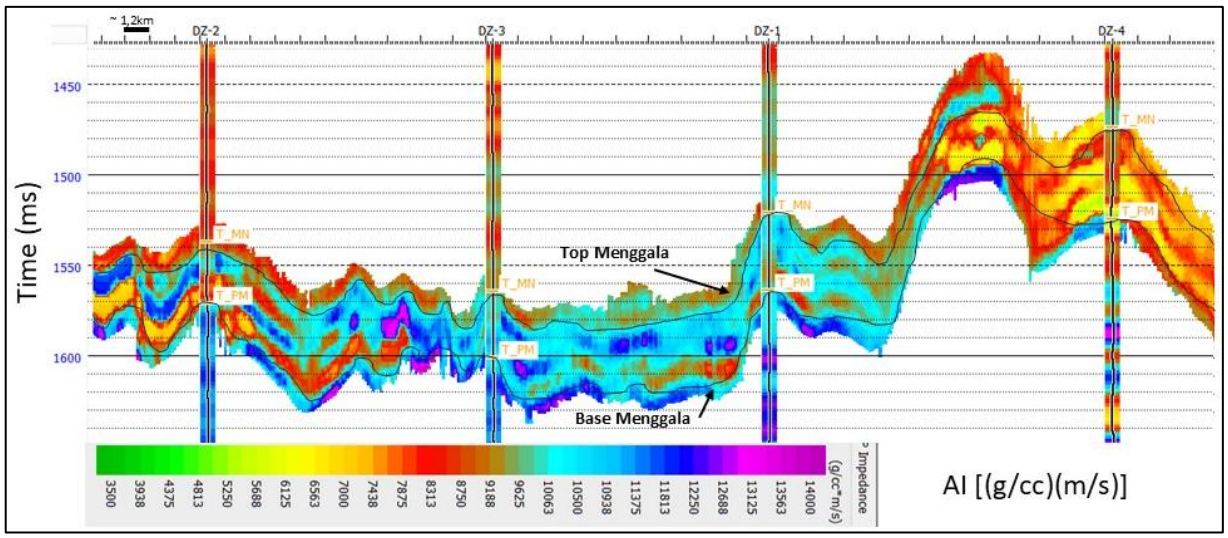


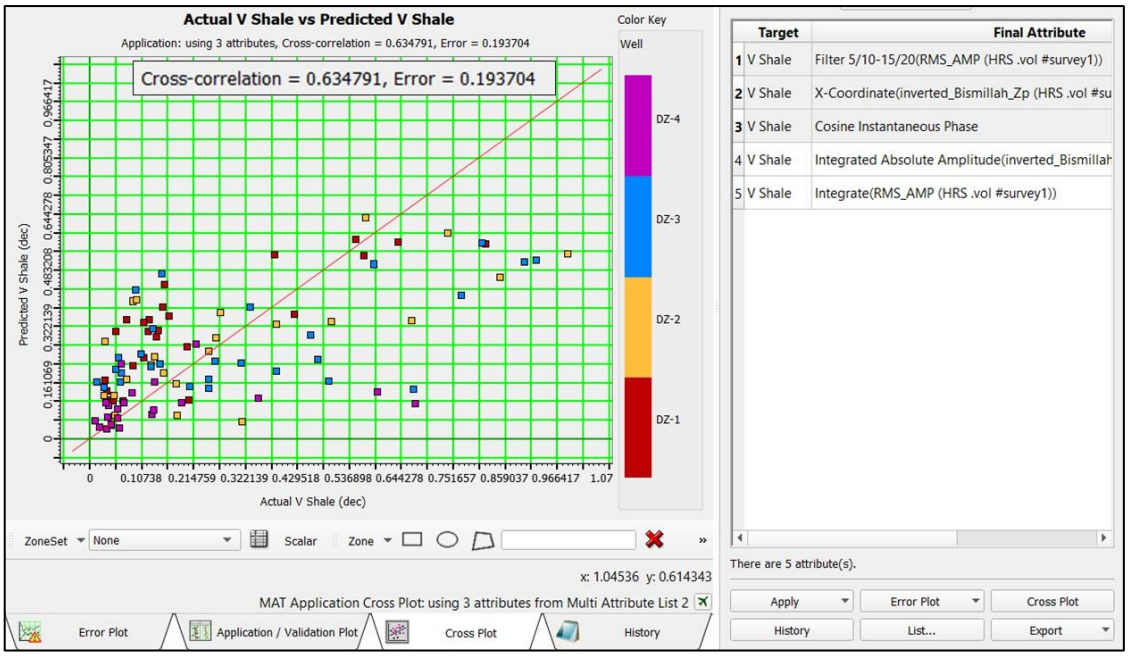
Figure 10. Acoustic Impedance Inversion Cross-Section

3.4 Seismic Multi-attribute Result

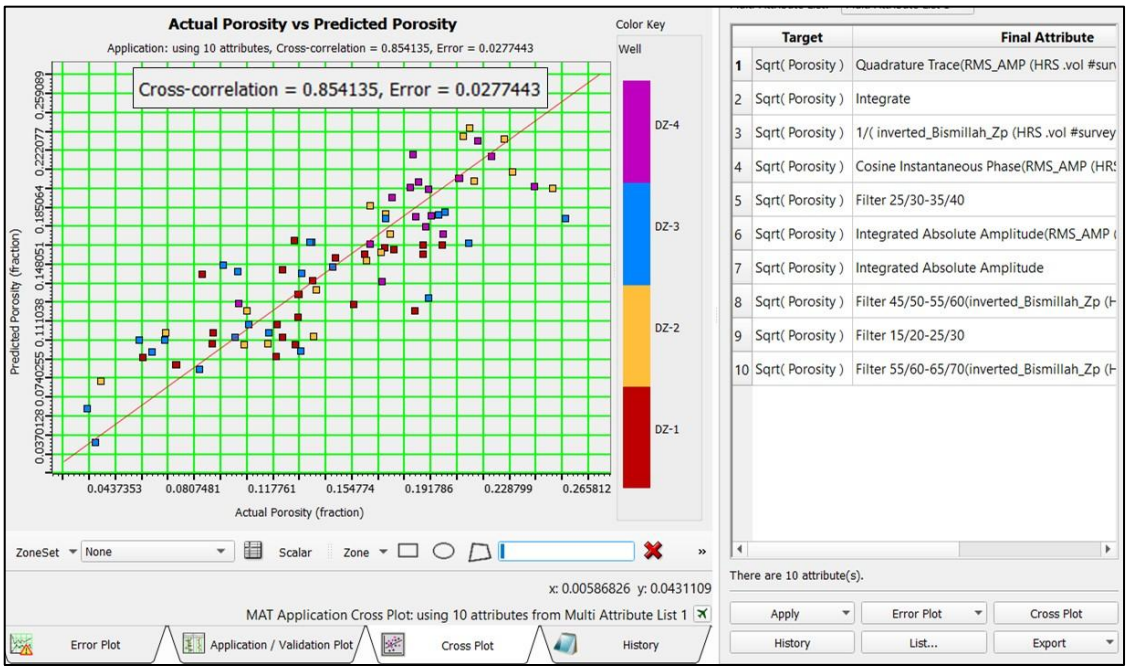
The multi-attribute regression analysis in this study was applied to predict Vshale and porosity (DPHI), with all four available wells serving as calibration points to ensure spatial representativeness of the resulting volumes. In contrast, water saturation (Sw) was not included as a target parameter in the multi-attribute workflow. This decision was driven by the fact that Sw log data, which are derived from resistivity measurements, are exclusively available at well DZ-4. Applying multi-attribute regression with only a single training well would yield a model that fits the training data well but lacks the predictive generalizability necessary for reliable spatial extrapolation, a condition commonly referred to as in-sample overfitting.

The multi-attribute seismic results for Vshale prediction in Figure 11(a) show a fairly good correlation between actual and predicted values, with a cross-correlation of 0.63 and an error of approximately 0.193. These values indicate that the multi-attribute model is capable of capturing the primary trend of shale distribution despite deviations at some data points, which are likely caused by lithological heterogeneity and the limitations of seismic resolution regarding changes in thin beds. In general, the crossplot results show a data distribution pattern that remains linear with the trend line, so this multi-attribute method is considered sufficiently representative for mapping Vshale variations in this target area.

A cross-plot analysis between acoustic impedance (AI) inversion and effective porosity (Figure 3) yielded a weak correlation coefficient of 0.407, indicating that AI inversion alone is insufficient to adequately capture the petrophysical relationships in the Menggala Formation target area. This poor correlation underscores the limitations of single-attribute inversion in representing reservoir heterogeneity, necessitating a more robust prediction approach. To address this limitation, multi-attribute seismic analysis was employed, and the results (Figure 11(b)) demonstrated substantial improvement in estimation quality, as reflected by a cross-correlation value of 0.85 and an error value of approximately 0.027. The high correlation coefficient confirms that the multi-attribute model is able to consistently produce a good relationship between seismic attributes and effective porosity, thus providing reliable prediction results for mapping porosity distribution across the target area.



(a)



(b)

Figure 11. (a) Crossplot Actual Vshale vs Predicted Vshale, (b) Crossplot Actual Porosity vs Predicted Porosity

On the seismic section resulting from the Vshale prediction in Figure 12(a), the target zone is bounded by the Top Menggala and Base Menggala zones, where a dominance of green to yellow colors is shown. When aligned with the scale bar on the right, this dominance of green to orange colors corresponds to a Vshale interval of 0.018–0.22, indicating low to moderate Vshale values. This condition suggests that the target zone is laterally dominated by relatively clean to slightly shaly sandstone, making this area a potential candidate for a high-quality reservoir. However, in certain sections, an increase in color toward dark blue-purple (0.33–0.45) is observed, indicating an increase in shale content, thereby confirming facies heterogeneity and the potential for interbedded sand-shale development in some areas. Thus, these multi-attribute results can be used to identify the

distribution of cleaner reservoir zones and to map areas with increased shale content as an indication of changes in the depositional environment.

In the multi-attribute seismic cross-section resulting from the porosity prediction (Figure 12(b)), the target zone interval bounded by Top Menggala and Base Menggala shows lateral variations in porosity. The target zone is generally dominated by low to moderate porosity values, indicated by yellow to orange hues ranging from 0.12 to 0.18. However, certain specific areas exhibit higher porosity values, indicated by a color shift toward blue and purple (porosity values of 0.3–0.4). This indicates the development of sandstone reservoirs with better quality in certain sections, while areas with lower porosity reflect the influence of increased shale content, compaction, or facies changes toward a finer-grained environment. Overall, these results indicate that the target interval has more varied reservoir potential and confirm the heterogeneity of porosity distribution within this target zone.

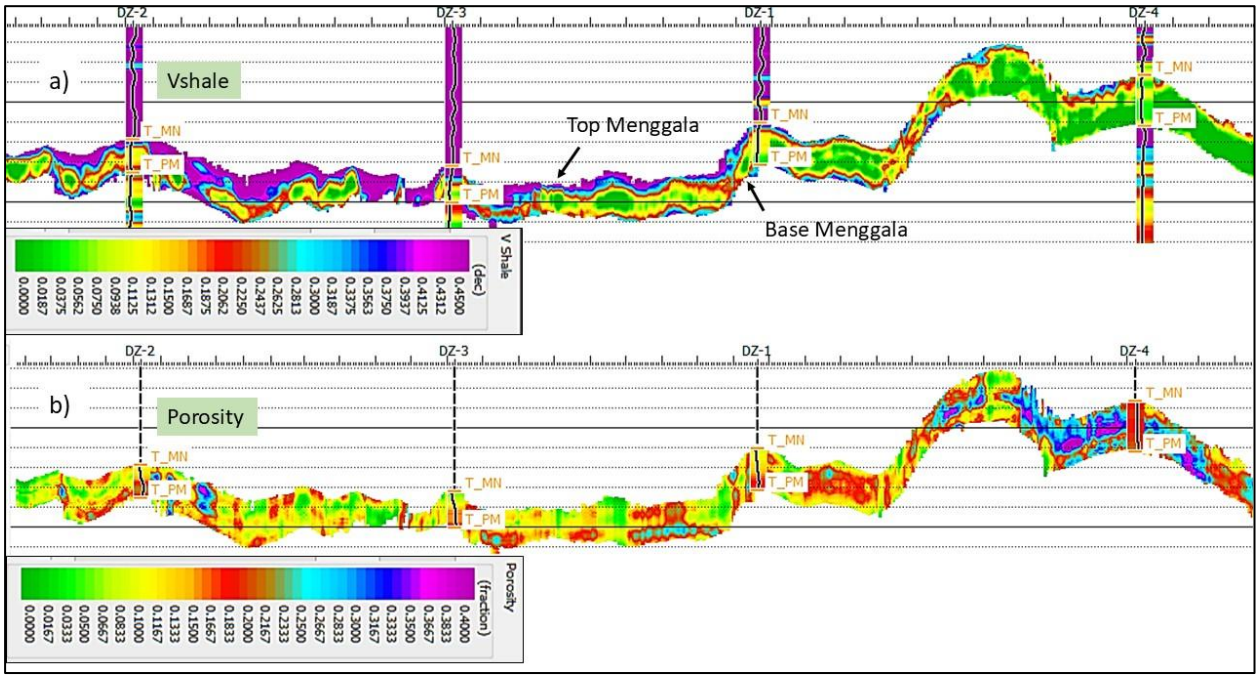


Figure 12. (a) Seismic Multiattribute Vshale Cross-section, (b) Seismic Multiattribute Porosity Cross-section

The performance of the multi-attribute seismic regression in this study is reflected by a moderate predictive correlation for Vshale (r = 0.63) and a strong correlation for porosity (DPHI) (r = 0.85). Contextualizing these results within the broader literature on the Central Sumatra Basin, the findings are consistent with previous investigations demonstrating that multi-attribute seismic methods outperform conventional single-attribute inversion in predicting petrophysical properties. Notably, (Huda et al., 2013) established that multi-attribute regression yields reliable estimates of reservoir characteristics in the Pematang Formation under conditions of sandstone heterogeneity, a setting comparable to that of the Menggala Formation in this study. Furthermore, (Wibowo et al., 2020) confirmed that the integration of multiple seismic attributes through stepwise regression substantially improves the ability to discriminate lithological variations across the reservoir interval.

Against this backdrop, the moderate Vshale correlation obtained here is interpreted as a consequence of the inherent vertical resolution limitations of post-stack seismic data, compounded by the thin-bedded, interbedded sand–shale character of the Menggala Formation that lies below the effective seismic resolution threshold. The strong DPHI correlation, on the other hand, indicates that the selected attributes are sensitive to the dominant acoustic impedance contrasts driven by porosity variation, thereby validating the applicability of the multi-attribute framework for subsurface reservoir characterization in Field X.

4. CONCLUSION

The study of sandstone reservoir characterization in the Menggala Formation of the Central Sumatra Basin using multi-attribute seismic methods yielded reliable interpretations. Based on petrophysical analysis of four wells (DZ-1 to DZ-4), the target interval is generally dominated by clean to slightly shaly sandstone. The average Vshale value was 0.166, the average density porosity (DPHI) was 0.155, indicating overall moderate reservoir quality with lateral heterogeneity likely controlled by depositional facies variations. Water saturation (Sw) analysis was restricted to well DZ-4, yielding an average Sw of 0.610, suggesting predominantly water-bearing conditions with several localized low-Sw intervals that may indicate hydrocarbon potential.

Acoustic impedance inversion results within the target interval range from 8,737 to 11,081 [g/cm^3·m/s] with an average reservoir thickness of approximately 75.47 m, indicating the presence of relatively porous sandstone zones. Multi-attribute seismic linear regression was successfully applied to predict the lateral distribution of Vshale and porosity (DPHI), producing cross-correlation values of 0.63 for Vshale and 0.85 for porosity, which are considered adequate for supporting reservoir characterization. Integration of these predicted volumes indicates that potential reservoir zones in the Menggala Formation are characterized by relatively low Vshale and higher porosity values, particularly in the central to right part of the seismic section near the fault zone, which may form structural traps. These results provide a useful reference for prospect identification and support future exploration and development planning in the Central Sumatra Basin.

ACKNOWLEDGEMENTS

The author sincerely thanks Mr. Handoyo for his guidance, insightful discussions, and valuable supervision throughout this research. The author also acknowledges PT Techwin South Betung for providing the seismic and well log data, as well as for granting permission to use data for this study and its publication.

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