

Multi-Attribute Analysis and Probabilistic Neural Network (PNN) Method for Predicting Carbonate Volume and Water Saturation in Biogenic Gas Reservoir: A Case Study of the Nias Basin, North Sumatra

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Abstract

Carbonate reservoirs frequently exhibit high heterogeneity, complicating the lateral prediction of petrophysical properties from sparse well log data. This study evaluates the hydrocarbon potential of a biogenic gas-bearing carbonate reservoir in the 'RC' Field, Nias Basin, by integrating well log and 2D seismic data. A multi-attribute analysis was conducted to identify seismic attributes sensitive to reservoir properties, which were subsequently used as input to a Probabilistic Neural Network (PNN) algorithm to predict the lateral distribution of Carbonate Volume (V_{cr}) and Water Saturation (S_w). Results identify a prospective gas-bearing carbonate zone in Well S-1 at depths of 4990 – 5693 ft, characterized by favorable reservoir quality and water saturation values predicted by the PNN model, with an average 0.4 (v/v). The PNN model significantly improved prediction accuracy, achieving correlation coefficients of 0.88 for Carbonate Volume and 0.83 for Water Saturation. These findings demonstrate that the PNN method effectively captures non-linear relationships between seismic attributes and petrophysical parameters, providing a robust framework for mapping prospective biogenic gas zones and optimizing future exploration planning in the Nias Basin.

Keywords: Biogenic Gas; Carbonate Reservoir; Carbonate Volume; Probabilistic Neural Network; Water Saturation.

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Introduction

In response to increasing energy demand and declining conventional hydrocarbon production, this study aims to evaluate the potential of hydrocarbon resources in the Nias Basin, North Sumatra. This situation encourages ongoing exploration efforts to discover new hydrocarbon resources.

Evaluating the hydrocarbon potential of carbonate reservoirs containing biogenic gas in the "RC" Field in the Nias Basin presents an exploration challenge. Carbonate reservoirs generally exhibit high

levels of heterogeneity due to depositional processes, diagenesis, and porosity development. Consequently, the lateral distribution of petrophysical properties is difficult to characterize accurately with limited well data.

To address these challenges, well-log and seismic data were integrated to obtain a more representative distribution of reservoir properties and better characterize lateral reservoir variability. Water Saturation (S_w) and Carbonate Volume distributions were predicted using a multi-attribute seismic analysis with the

Probabilistic Neural Network (PNN) algorithm. Previous research by Khan et al. (2025) and Durrani et al. (2020) shows that the Probabilistic Neural Network (PNN) method provides more accurate predictions of petrophysical properties and characterizes reservoir heterogeneity more effectively than conventional approaches, making it well-suited for complex carbonate reservoirs.

Characterizing carbonate reservoirs in forearc settings, such as the Nias Basin in North Sumatra, remains a significant challenge due to the complex nature of carbonate diagenesis and the inherent heterogeneity of the rocks. Although previous studies, such as Rifai et al. (2019), have successfully characterized reservoir properties in this region using conventional seismic inversion methods, this approach is often limited in its ability to map heterogeneity within carbonate systems. Deterministic inversion techniques generally produce overly smoothed models that often fail to capture the complex nonlinear relationships between seismic attributes and petrophysical parameters, leading to estimates that overlook local variations in these carbonate features. This study addresses this gap by applying the Probabilistic Neural Network (PNN) method. By minimizing prediction bias in highly heterogeneous reservoir zones, this method improves the accuracy of carbonate volume and water saturation predictions, thereby providing better spatial resolution for identifying exploration targets (Ardinda & Riyanto, 2020).

Materials and Methods

This study comprises four main processing stages to estimate the spatial distribution of reservoir petrophysical properties. The first stage involves reservoir marker identification through well-log sensitivity analysis using crossplot log, which defines the target reservoir intervals based on the relationships among petrophysical

parameters. The second stage involves calculating Water Saturation (Sw) and Carbonate Volume from well-log data to quantify reservoir properties within the identified intervals. These results provide the reference data for subsequent seismic-based prediction. The third stage consists of multi-attribute analysis to identify the seismic attributes most sensitive to the target petrophysical parameters. The selected attributes are evaluated for their correlation with well-log data to determine the optimal attribute combination for predicting reservoir properties. Probabilistic Neural Network (PNN) was trained using the selected seismic attributes and the corresponding log-derived Water Saturation (Sw) and Carbonate Volume values from Wells S-1 and T-1. During training, the PNN learned the nonlinear relationship between the seismic attributes and the log-derived reservoir properties. Model performance was evaluated by comparing the PNN-predicted log values with the corresponding measured well-log values using linear regression. The reported correlation coefficients were calculated from the regression of the predicted on the measured reservoir properties and were used to assess the predictive capability of the PNN model. Finally, a multi-attribute Probabilistic Neural Network (PNN) is applied to predict the lateral distribution of Water Saturation and Carbonate Volume across the seismic sections. By integrating seismic attributes with well-log data, the PNN models the complex relationship between seismic responses and petrophysical properties, enabling reliable prediction of reservoir properties in areas lacking well control (Sinaga et al., 2019). The workflow of the present study is illustrated in Figure 1.

Geological Setting

The Nias Basin is part of the Sumatran forearc basin within the Sunda subduction system and developed from the Early Eocene to the Late Pleistocene. The basin plays a significant geomorphological and

tectonic role as the rear boundary of compressional deformation associated with subduction processes, while forming the structural and geomorphological transition between uplifted and subsiding regions. Several major fault systems, such as the

Batee and Mentawai Faults, cross the Nias Basin. These faults developed as a result of the oblique subduction of the northward-moving Indo-Australian Plate beneath the Eurasian Plate (Wibowo et al., 2024).

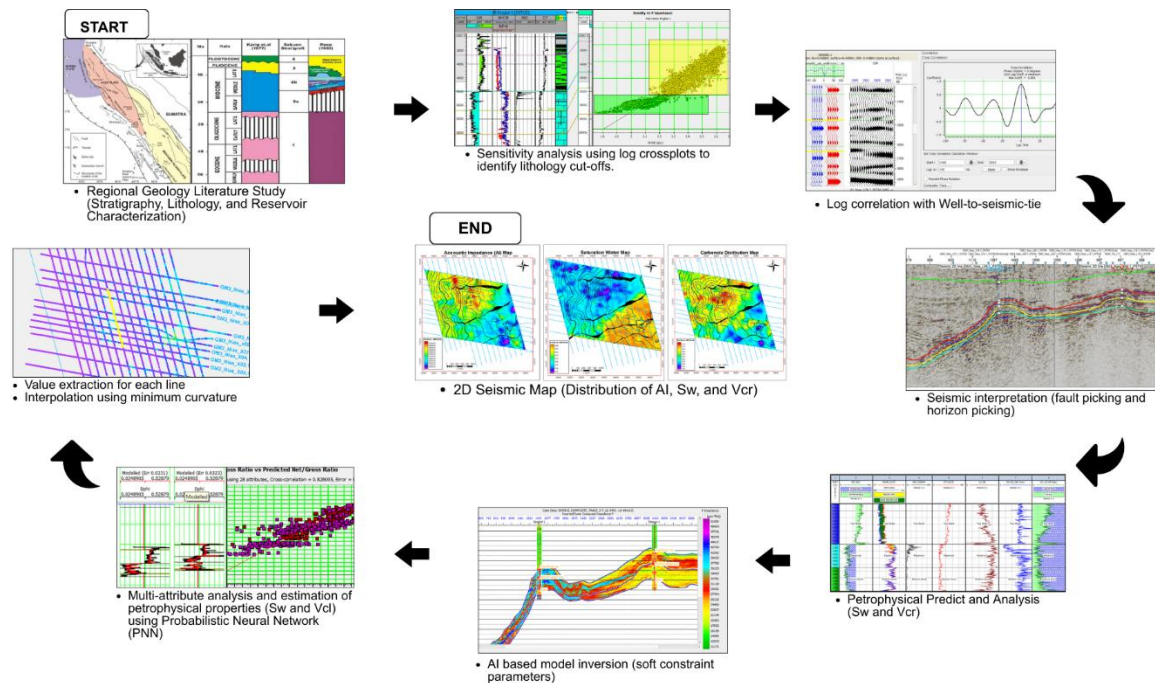


Figure 1. Research Workflow.

The regional geological structure is dominated by northwest–southeast trending extensional and transtensional faults that control the development of sub-basins, sedimentation patterns, and structural deformation within the Nias Basin. On a regional scale, basin deformation is also influenced by the Batee Fault and the Mentawai Fault Zone, which developed parallel to the Sunda subduction zone and are characterized by dextral strike-slip movement (Wibowo et al., 2024). As part of the forearc basin system, the location of the Nias Basin between Sumatra Island and the Indian Ocean contribute to a relatively low geothermal gradient, with an average shallow heat flow of approximately 1.2 HFU (Haris et al., 2020).

According to the Geological Map of Nias, the study area belongs to the Gomo Formation. These formations are composed of claystone, marl, sandstone, limestone with tuff, tuff and peat inserts. Based on the

fossil content, the age of this formation is Early Miocene to Middle Pliocene (Rifai et al., 2019). The stratigraphic framework of the study area is presented in Figure 2.

The stratigraphy of the study area is shown in Table 1 and ranges in age from Middle Miocene to Early Pleistocene.

Biogenic Gas

Biogenic gas is commonly found in deltaic environments and is typically trapped within Quaternary sedimentary rocks. This type of gas is predominantly methane, produced through microbial activity under relatively low temperatures (Astawa et al., 2016). The biogenic gas formation process begins with the decomposition of organic material by bacteria, which then produces gas dissolved in pore water (Dewanto et al., 2020). When the dissolved gas concentration exceeds the saturation limit, the gas migrates and forms biogenic gas accumulations (Astawa et al., 2016).

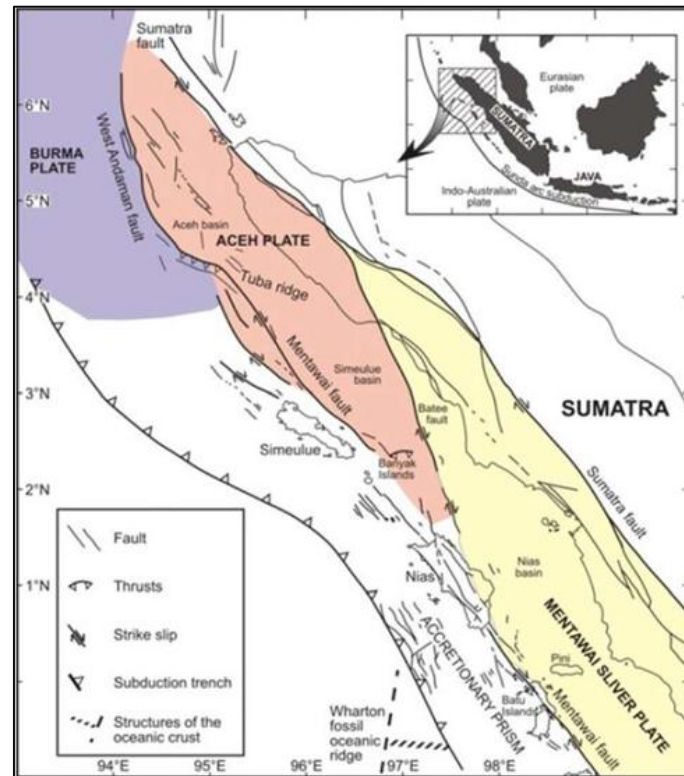


Figure 2. Geological setting modified by Haris et al., (2020) and Base Map 2D Seismic Lines.

Table 1. Stratigraphy of the Nias Basin, the study area is highlighted by the red box (Rifai et al., 2019).

Ma	Kala	Karig et.al (1977)	Sekuen Stratigrafi	Rose (1983)	Play Hidrokarbon	Cenozoic Cycle Chart Vail et.al (1977)
						Rising ← Falling
	PLEISTOCENE		4	Regressive Clastic Unit	Mio-Pliocene	
	PLIOCENE		3	Transpressive Clastic Unit	Wegde Top	
10	MIOCENE LATE		2b	Transpressive Clastic Unit	Miocene Wegde Middle	
20	MIOCENE EARLY		2a	Transpressive Clastic Unit		
30	OLIGOCENE LATE					
40	OLIGOCENE EARLY					
50	Eocene		1		Pre-Neogene Wegde Base	
						Present sea level

Acoustic Impedance Inversion

Seismic inversion is fundamentally influenced by several key factors, such as the quality of the well-to-seismic tie, the accuracy of horizon picking, the results of wavelet extraction, and the initial model used (Abdulaziz, 2020). In this study, a model-based seismic inversion method was

applied to estimate Acoustic Impedance (AI) by integrating an initial low-frequency impedance model with seismic reflection data to produce a high-resolution AI model consistent with both well-log and seismic data (Shakir et al., 2024). The creation of the initial impedance model and the determination of parameters are based on

subsurface conditions that reflect variations in rock lithology (Lestari et al., 2023). A statistical wavelet extraction method was employed to generate a representative seismic wavelet for the inversion process. The extracted wavelet has a dominant frequency of 23 Hz, corresponding to an estimated wavelength of approximately 200 ft within the target interval. The quality of the well-to-seismic tie was evaluated prior to inversion. For Well S-1, the synthetic and seismic traces achieved a correlation coefficient of 0.639 with a 0-time shift, whereas Well T-1 yielded 0.566 with a 0-time shift. These correlation values indicate an acceptable match between the synthetic and seismic data.

The Acoustic Impedance (AI) was calculated using the Equation (1):

$$AI = V_p \cdot \rho \quad (1)$$

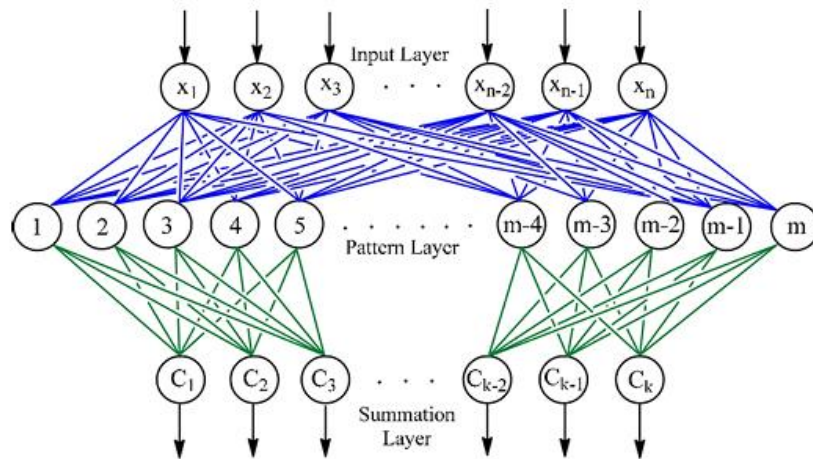


Figure 3. Illustration of the Probabilistic Neural Network (PNN) working mechanism (Ahangarani et al., 2022).

$$f_i(x) = g_i(x) = \frac{1}{(2\pi)^{\frac{\rho}{2}}(\sigma^\rho)} \cdot \frac{1}{M_i} \sum_{j=i}^{M_i} \left[\exp \left(-\frac{\left((x - x_{ij})^T \cdot (x - x_{ij}) \right)}{2 \cdot \sigma^2} \right) \right] \quad (2)$$

The functions $f_i(x)$ or $g_i(x)$ are used to represent the probability response for each i -th class, where $i = 1, 2, \dots, K$. In this equation, T denotes the transpose operation. The index i represents the number of analyzed classes, while the index j indicates the number of samples or data points within each class. The variable X_{ij} refers to the j -th training data vector

where AI is acoustic impedance (g/cc)·(ft/s), ρ is density (g/cc), and V_p is P-Wave velocity (ft/s) (Erryansyah et al., 2020).

The results of this acoustic impedance measurement will later be used as an external attribute in the Probabilistic Neural Network (PNN) method.

Probabilistic Neural Network (PNN)

Reservoir parameter predictions are made by integrating well-log interpretations with both internal and external seismic attributes using the Probabilistic Neural Network (PNN) method illustrated in Figure 3. The functional equation of the PNN algorithm proposed by Wenando et al. (2023) is given in Equation (2).

belonging to the i -th class, whereas x represents the test data vector to be predicted, such as seismic attribute data at a specific location. Furthermore, M_i denotes the number of training samples in the i -th class, and ρ represents the dimensionality of a vector x , which is generally associated with the number of attributes used in the analysis. The parameter σ is the smoothing

parameter that controls the spread of the probability function, thereby influencing the model's sensitivity to data variations. In this study, the smoothing parameter (σ), which controls the spread of the Gaussian function and the sensitivity of the PNN to the training data, was determined during the PNN training process. The optimal smoothing value was selected by maximizing the correlation coefficient from linear regression while minimizing the prediction error between PNN-predicted and log-derived reservoir properties (Mohebbi et al., 2020).

This study utilized a dataset comprising 27 post-stack time-migrated 2D seismic lines and two wells (S-1 and T-1) from the study area. The seismic basemap, showing the distribution of the seismic lines and well locations, is presented in Figure 2. The Probabilistic Neural Network (PNN) algorithm consists of several components: the input layer, the pattern layer, and the summation layer. During training, the PNN learns the relationship between well-log data and seismic attributes around the well, which is then used to estimate the distribution of reservoir parameters in data-free areas (Abdulaziz, 2020). During training, the PNN algorithm performs several trials to determine the optimal combination of seismic attributes, which is evaluated using the correlation coefficient between the predicted results and well-log data. The combination with the highest correlation and lowest error is selected as the best model (Joshi & Sain, 2021). This approach enables the lateral mapping of porosity, water saturation, and carbonate volume distribution on 2D seismic data, thereby providing a more comprehensive picture of subsurface reservoir characteristics.

Petrophysics Evaluation

Petrophysical evaluation is carried out to characterize the reservoir's physical properties using parameters such as shale

volume (VSH), porosity, water saturation (Sw), and Carbonate Volume (Vcr).

The calculation of shale volume (Vsh) in this study was performed using Gamma Ray (GR) logs with the Gamma Ray Index (IGR) approach, as shown in Equation (3). This method was used as the basis for estimating shale content by utilizing the GR response as the primary indicator of lithology (Jassam et al., 2023).

$$VSG = IGR = \frac{GR_{log} - GR_{min}}{GR_{max} - GR_{min}} \quad (3)$$

The total porosity (ϕ_T) values within the reservoir zone were calculated based on density log (RHOB) data using the Equation (4) by Saadu & Nwankwo (2018):

$$\phi_T = \frac{\rho_{matrix} - \rho_{log}}{\rho_{matrix} - \rho_{fluid}} \quad (4)$$

To obtain effective porosity, an approach is used that corrects total porosity for the influence of shale, as shown in Equation (5) (Tariq et al., 2023):

$$\phi_{eff} = \phi_T \cdot (1 - V_{shale}) \quad (5)$$

Water saturation (Sw) is a petrophysical parameter that measures the proportion of pore space occupied by water in the rock matrix. This parameter plays a crucial role in reservoir evaluation, as it is directly related to the presence of hydrocarbons. In this study, water saturation was determined using the Equation (6) (Schön, 2015) as shown below:

$$S_w = \frac{1}{2} \cdot \frac{R_w}{\phi^m} \left[\sqrt{\frac{4\phi^m}{R_w \cdot R_t} + \left(\frac{V_{sh}}{R_{sh}}\right)^2} - \frac{V_{sh}}{R_{sh}} \right] \quad (6)$$

The parameters used in this calculation include porosity (ϕ), formation resistivity (R_t), formation water resistivity (R_w), shale volume (V_{sh}), shale resistivity (R_{sh}), and the cementation exponent (m), which represents the relationship between

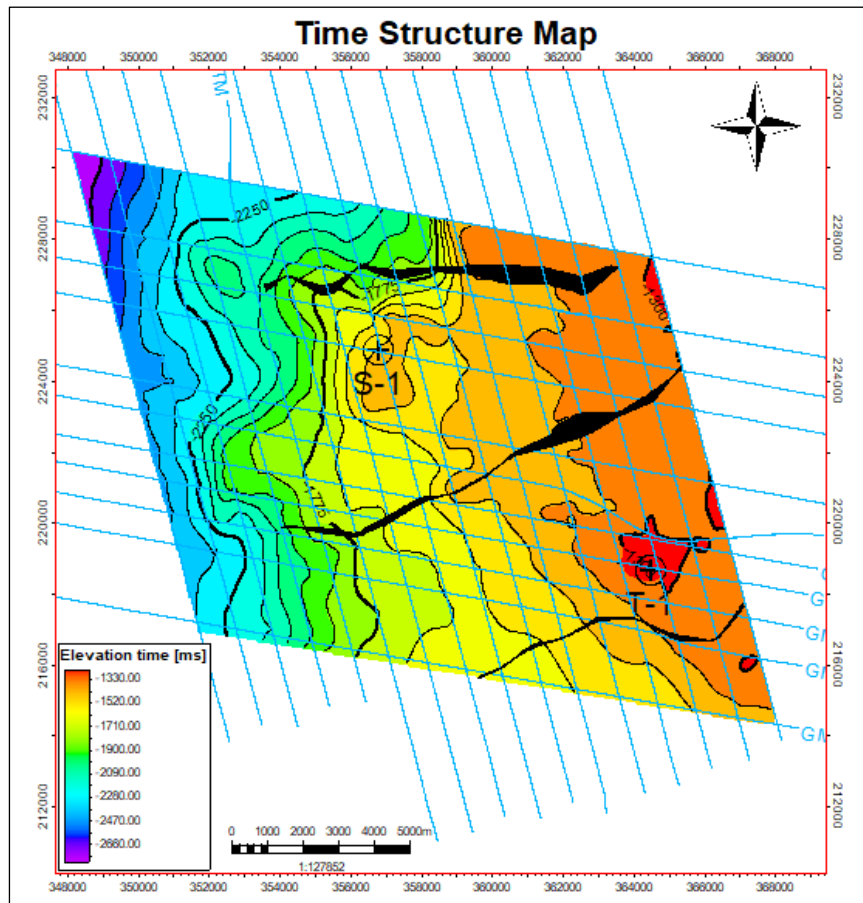
porosity and the electrical resistivity response of the rock matrix.

Furthermore, the Carbonate Volume (V_{cr}) is a parameter that describes the proportion of rock that is relatively clean of shale. This parameter is used to identify the distribution of rocks that have the potential to function as reservoirs, as increasing shale content is generally associated with decreased reservoir quality due to lower porosity and effective permeability. The calculation of Carbonate Volume (V_{cr}) is given by Equation (7).

$$V_{cr} = 1 - V_{shale} \quad (7)$$

Result and Discussion

The Time Structure Map (TSM) at Well S-1 as shown in Figure 4 indicates that the well is located within a carbonate buildup structure at a two-way travel time of approximately 1520 ms. The high-relief contours surrounding Well S-1 are interpreted as potential hydrocarbon accumulation zones. Furthermore, the structural relief variations observed on the TSM reflect the relatively complex geological setting of the study area, which is likely to influence the subsurface distribution of reservoir properties. Petrophysical analysis was subsequently conducted to evaluate the distribution of Water Saturation (S_w) and Carbonate Volume within the study area.



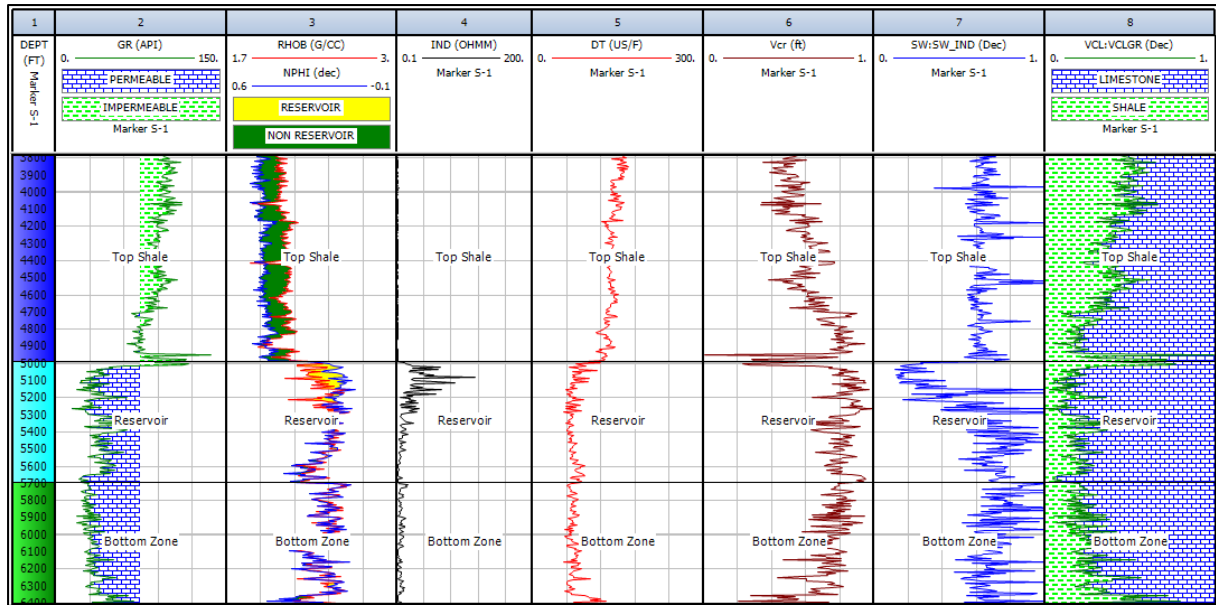


Figure 5. Petrophysical Log Interpretation of Well S-1: Carbonate Volume (V_{cr}), Water Saturation (S_w) and Shale Volume (V_{sh}).

Petrophysical analysis of reservoir intervals in the target area revealed contrasting reservoir characteristics between Wells S-1 and T-1. Well S-1 4990–5693 ft, exhibited several hydrocarbon indicators, including an RHOB–NPHI crossover and high resistivity values. The log-derived petrophysical analysis indicates a high Carbonate Volume of 0.76 (v/v) and a relatively low Water Saturation (S_w) of 0.4 (v/v) in the Top Reservoir. These characteristics indicate the presence of

porous carbonate rocks with pore spaces partially filled with hydrocarbons, as shown in Figure 5 for Well S-1.

In contrast, based on log-derived petrophysical analysis, Well T-1 4280–4864 ft exhibited higher Water Saturation (S_w) values 0.9 (v/v), lower resistivity, and no NPHI–RHOB crossover, indicating that the reservoir is largely saturated with water, as shown in Figure 6 for Well T-1

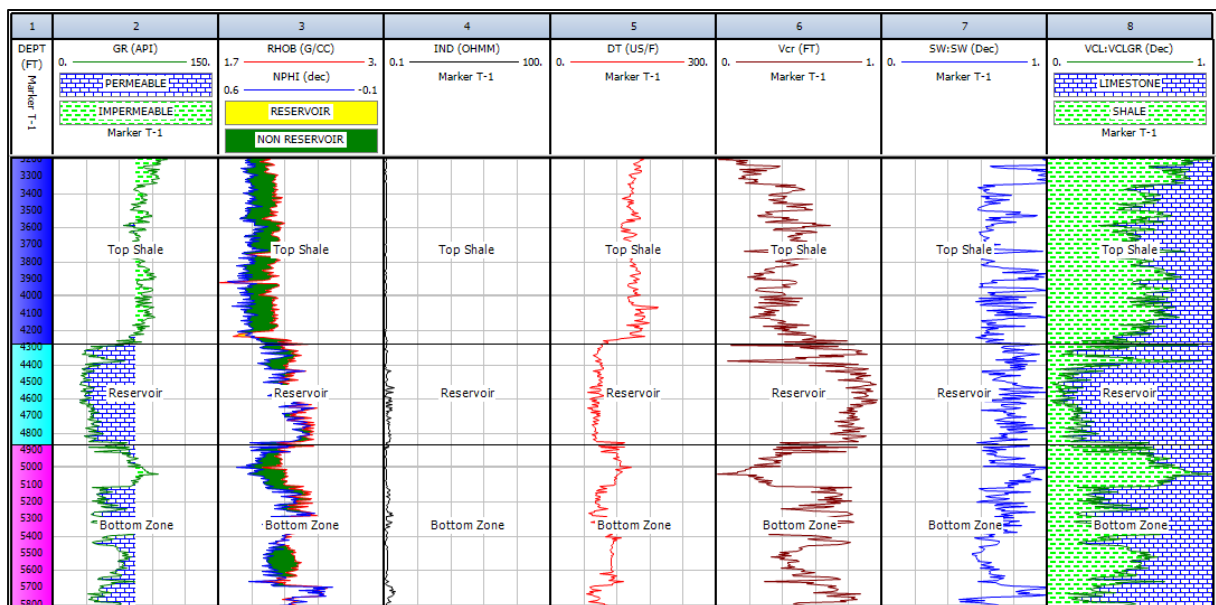


Figure 6. Petrophysical Log Interpretation of Well T-1: Carbonate Volume (V_{cr}), Water Saturation (S_w) and Shale Volume (V_{sh}).

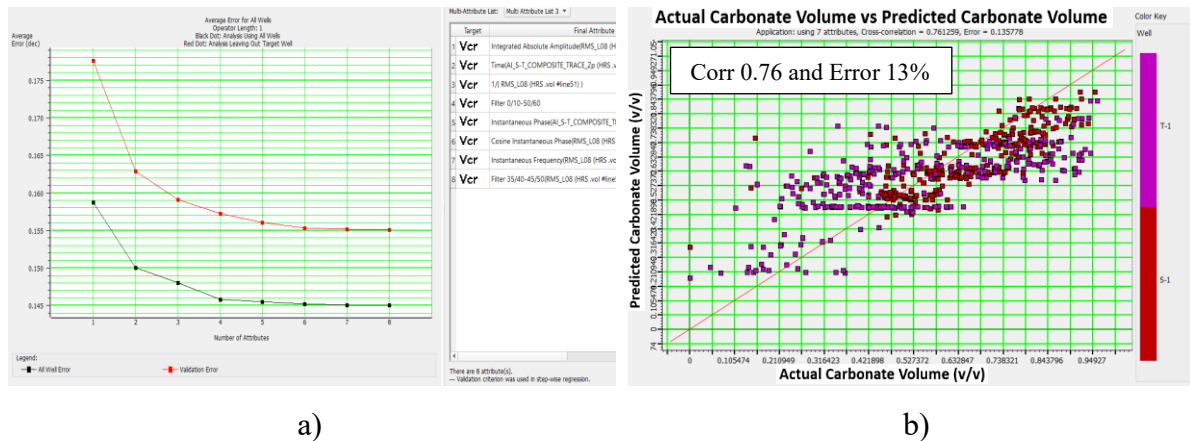


Figure 7. Carbonate Volume Prediction with Multi-Attribute Analysis; a) Attribute Training Curve of Vcr Prediction with 8 Attributes and b) Crossplot Actual Vcr (v/v) vs Predicted Vcr (v/v) using 7 Attributes.

Before applying the Probabilistic Neural Network (PNN) to reservoir property prediction, attribute training and multi-attribute analysis were conducted to identify the seismic attributes most sensitive to Water Saturation (S_w) and Carbonate Volume. Each seismic attribute was evaluated based on its correlation with well-log data, and the seven most effective attributes, including amplitude, frequency, phase, and external acoustic impedance, were selected. The significant prediction error obtained by using acoustic impedance indicates that it helps distinguish different lithologies and provides a more accurate characterization of carbonate reservoirs. The selected attribute combination provided a stronger representation of carbonate rock

properties than individual attributes, yielding a correlation coefficient of 0.76 and an error of 13% for Carbonate Volume prediction as shown in Figure 7. Since multi-attribute analysis is based on linear regression, its ability to capture the complex nonlinear relationship between seismic attributes and reservoir properties is limited. Therefore, the Probabilistic Neural Network (PNN) was employed to improve prediction accuracy. The PNN model produced more accurate predictions of Carbonate Volume and Water Saturation and generated a laterally continuous distribution that more effectively represents reservoir characteristics across the seismic section as shown in Figure 8.

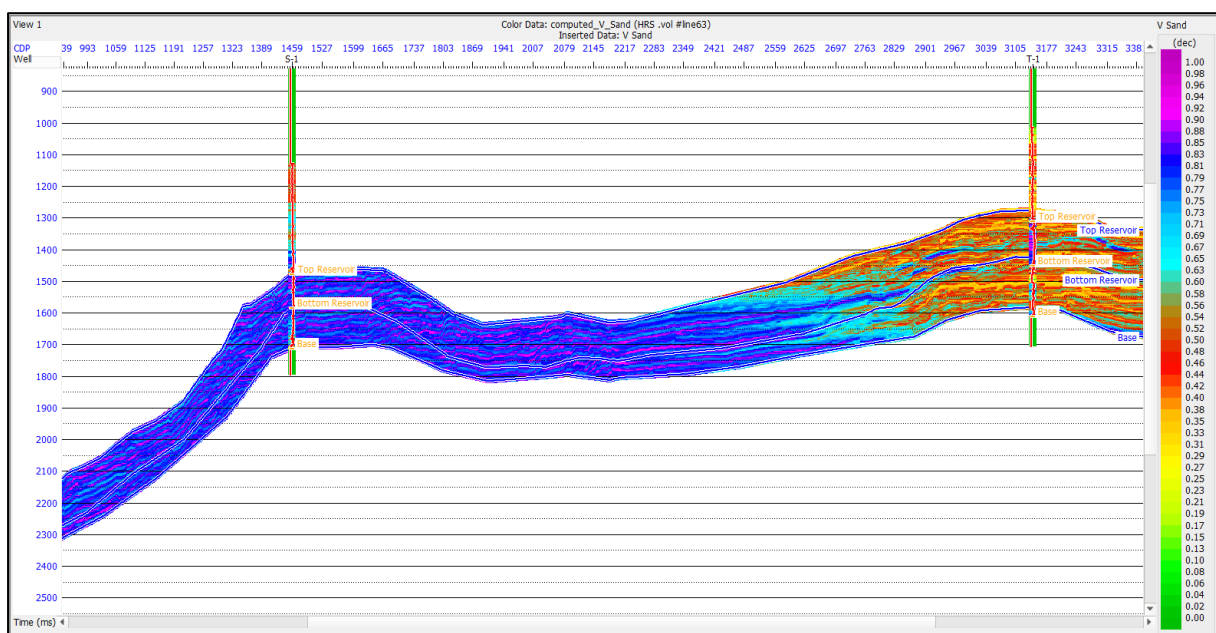


Figure 8. Carbonate Volume cross-section predicted using the PNN method.

The result shown in Figure 8 indicates that the application of the Probabilistic Neural Network (PNN) method improved the prediction accuracy of Carbonate Volume compared to the multi-attribute analysis. The validation error and crossplot results presented in Figure 8 show that the correlation coefficient increased to 0.88, while the prediction error decreased to 9%. These improvements indicate that the PNN model can better capture the nonlinear relationship between seismic attributes and

Carbonate Volume, resulting in predictions that are closer to the well-log data. The higher correlation coefficient and lower error demonstrate that the model accurately represents the Carbonate Volume distribution, with only minor deviations from the actual data. Therefore, the validation results confirm that the PNN model is reliable for predicting the spatial distribution of Carbonate Volume within the study area.

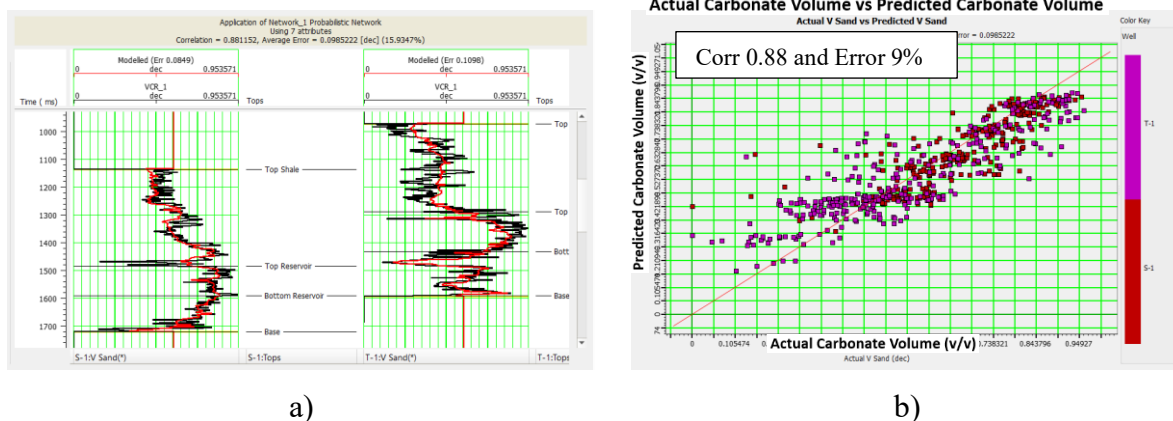


Figure 9. Carbonate Volume Prediction with Multi-Attribute Analysis; a) Attribute Training Curve of Vcr Prediction with 8 Attributes and b) Crossplot Actual Vcr (v/v) vs Predicted Vcr (v/v) using 7 Attributes.

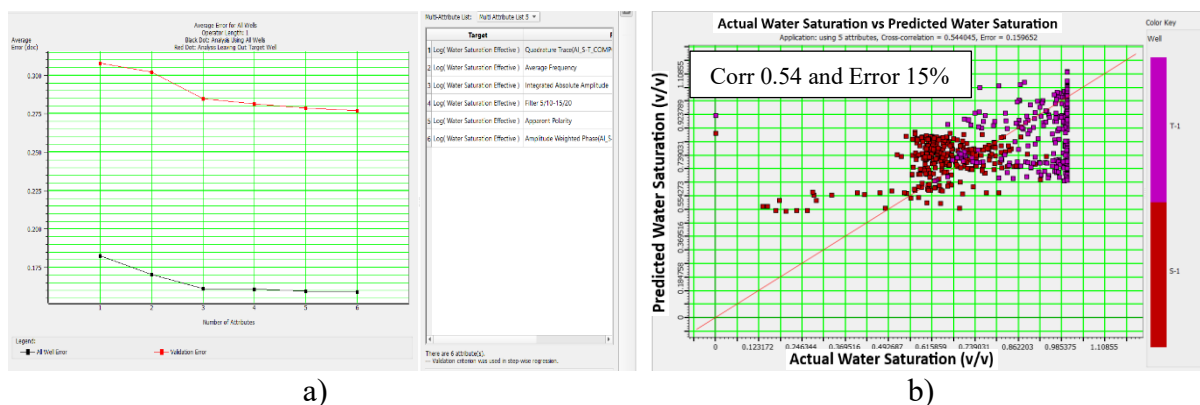


Figure 10. Water Saturation Prediction with Multi-Attribute Analysis; a) Attribute Training Curve of Sw Prediction with 6 Attributes and b) Crossplot Actual Sw (v/v) vs Predicted Sw (v/v) using 5 Attributes.

The estimation of Water Saturation (S_w) followed the same workflow as the Carbonate Volume prediction, beginning with attribute training and multi-attribute analysis, and then applying the Probabilistic Neural Network (PNN). Attribute training was carried out to identify the seismic attributes most sensitive to Water Saturation. Based on the results shown in Figure 10(a), five optimal attributes were

selected. These attributes were then used as input for the multi-attribute analysis to establish the relationship between the seismic attributes and Water Saturation. The results of the multi-attribute analysis, presented in Figure 10(b), yielded a correlation coefficient of 0.54 and an error of 15%, indicating that the relationship between the seismic attributes and Water Saturation remained relatively limited.

These results suggest that the regression-based approach was insufficient to accurately capture the spatial variation in Water Saturation across the study area. This limitation indicates that the relationship between seismic responses and Water Saturation is nonlinear and cannot be adequately represented using a regression-

based approach alone. Therefore, the Probabilistic Neural Network (PNN) was applied to capture these nonlinear relationships, resulting in improved prediction accuracy and a Water Saturation distribution that better represents the reservoir conditions throughout the study area.

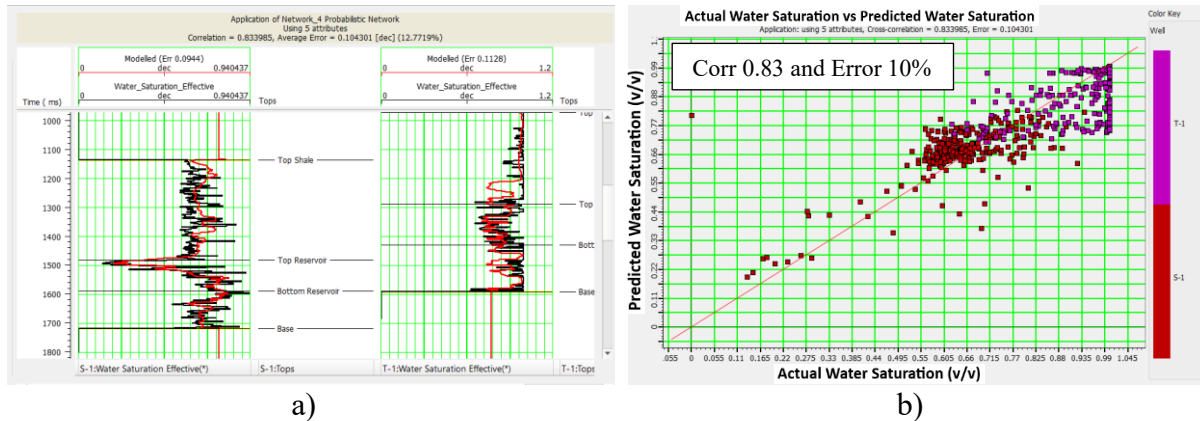


Figure 11. Water Saturation Prediction with Probabilistic Neural Network (PNN) Analysis; a) Attribute Training Curve of Sw Prediction with 6 Attributes and b) Crossplot Actual Sw (v/v) vs Predicted Sw (v/v) using 5 Attributes.

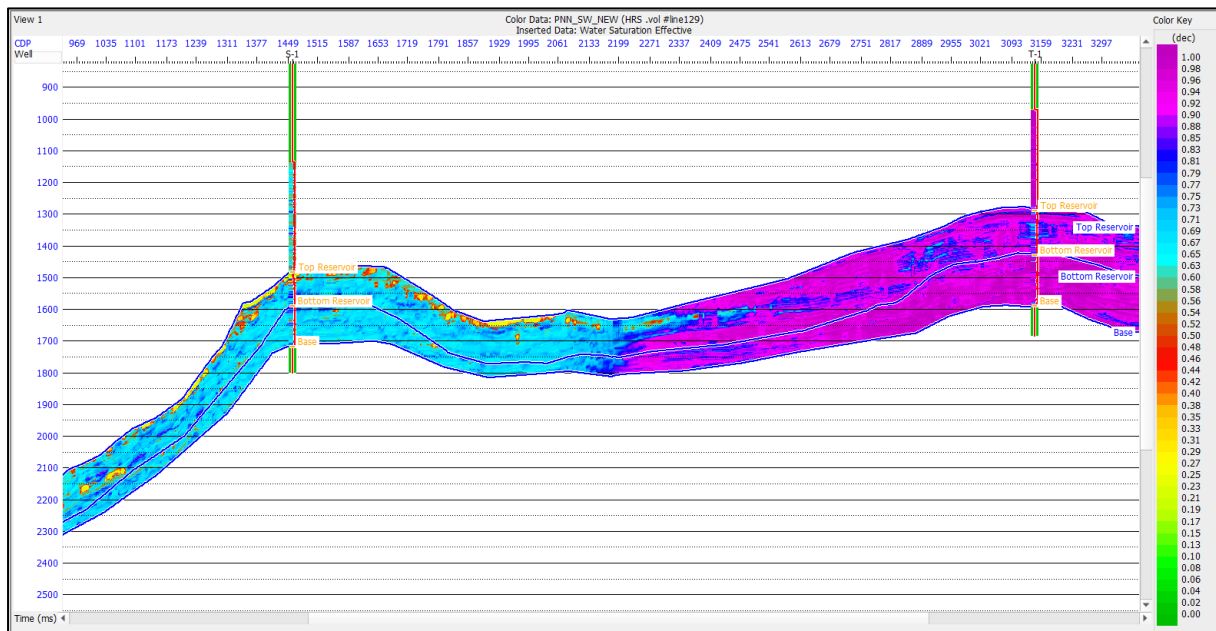


Figure 12. Water Saturation cross-section predicted using the PNN method.

Following the application of the Probabilistic Neural Network (PNN), the prediction accuracy of Water Saturation (Sw) improved compared with the results obtained from the multi-attribute analysis. The validation error and crossplot results presented in Figure 11 show that the correlation coefficient increased from 0.54

to 0.83, while the error value decreased from 15% to 10%. These improvements indicate that the PNN model is more effective in capturing the nonlinear relationship between the seismic attributes and Water Saturation, resulting in predictions that are in closer agreement with the well-log data. The higher correlation

coefficient and lower error further demonstrate that the PNN model provides a reliable estimation of Water Saturation within the target interval. The Water Saturation prediction generated from the five selected attributes yielded a distribution that is more representative of subsurface conditions. The predicted results indicate that Water Saturation is more dominant around Well T-1 than Well S-1 as shown in

Figure 12, suggesting that the area surrounding Well T-1 is predominantly saturated with water. Therefore, the application of the PNN method not only improved prediction accuracy compared with multi-attribute analysis but also produced a laterally continuous Water Saturation distribution that better represents the reservoir characteristics in the study.

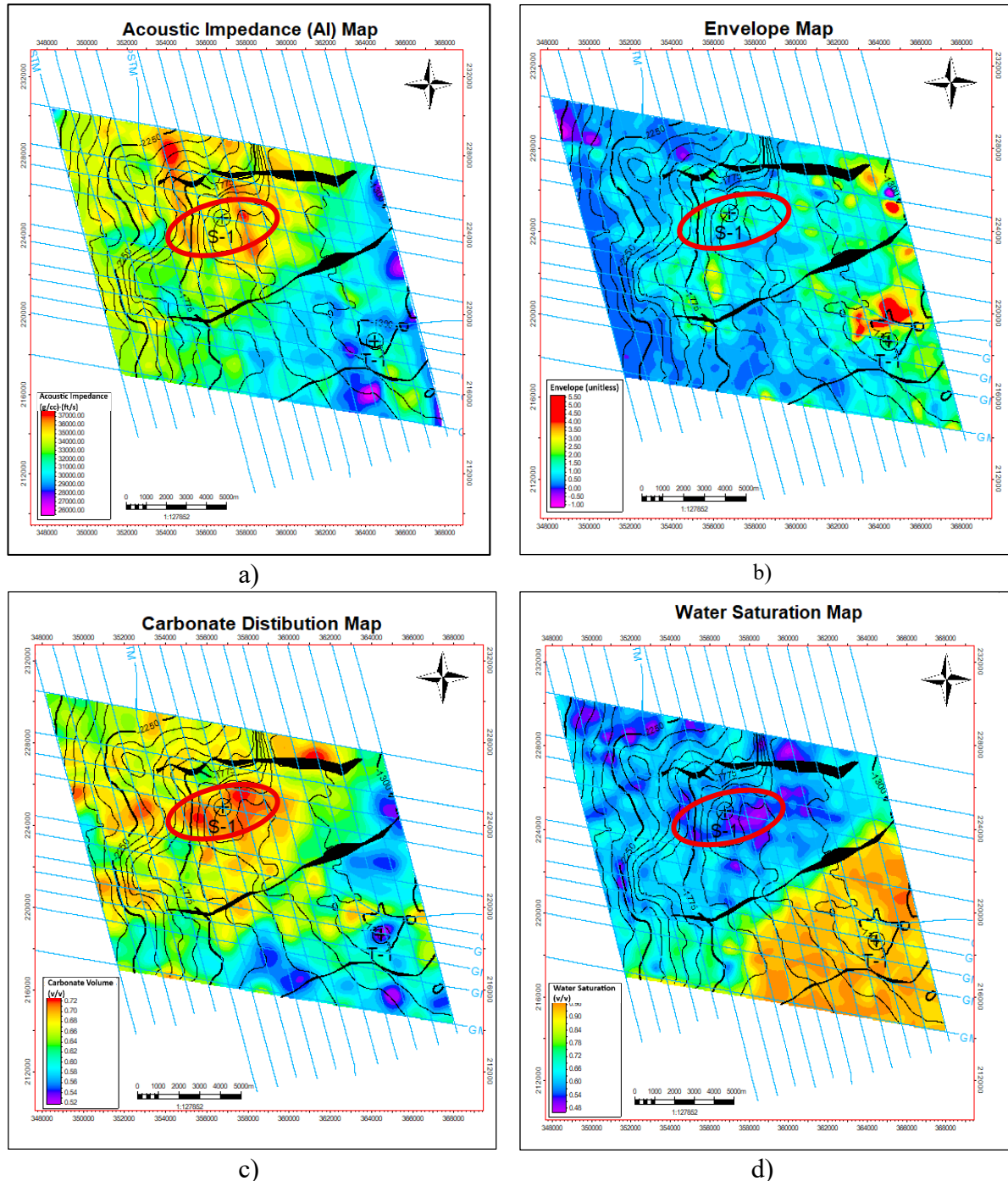


Figure 13. Distribution of variations value on the 2D seismic surface map, including a) Acoustic Impedance Map, b) Envelope Attribute Map, c) Carbonate Volume, and d) Water Saturation.

As shown in Figure 13(a), the Acoustic Impedance (AI) distribution indicates that AI values around Well S-1 range from 32,000 to 35,000 (g/cc)·(ft/s), whereas those around Well T-1 range from 28,000 to 31,000 (g/cc)·(ft/s), with a northwest–southeast orientation. According to the cutting samples data in the PPPGL (2018) report, the higher AI values observed around Well S-1 are attributed to the presence of pyrite within the reservoir interval. Because pyrite has a relatively high density, its presence increases the rock's bulk density, resulting in higher Acoustic Impedance values. In addition, carbonate lithologies generally exhibit higher Acoustic Impedance than clastic sedimentary rocks due to their higher density and more compact rock framework.

In the case of biogenic gas reservoirs in the Nias Basin, high envelope anomalies associated with low acoustic impedance values do not necessarily indicate the presence of hydrocarbons as shown in Figure 13(b). This interpretation is supported by well data from around Well T-1, which show water saturation (S_w) values close to 1 dec and relatively low Carbonate Volume values, indicating that the reservoir interval is predominantly occupied by formation water. Conceptually, the envelope attribute represents the magnitude of the reflection amplitude, regardless of signal polarity. Therefore, both positive and negative reflection amplitudes generated by interlayer acoustic contrast can produce high envelope responses. Consequently, strong impedance contrasts caused by lithological variations, porosity changes, or thin carbonate layers can produce high envelope anomalies that are not directly related to hydrocarbon accumulation. These anomalies are then interpreted as indicators of significant contrasts in rock physical properties, and the hydrocarbon interpretation must be supported by additional petrophysical parameters.

As shown in Figure 13(c), the predicted Carbonate Volume distribution indicates that the area surrounding Well S-1 exhibits better reservoir quality than Well T-1. Based on the PNN model, the average Carbonate Volume was predicted to be 0.76 (v/v) around Well S-1, whereas the average Carbonate Volume around Well T-1 was 0.50 (v/v). The relatively higher Carbonate Volume values in Well S-1 indicate a greater proportion of effective reservoir intervals, dominated by clean carbonate rocks with low shale content. In contrast, the lower Carbonate Volume values observed around Well T-1 are associated with lithologies such as claystone and calcilutite, which contain higher shale content and consequently reduce reservoir quality. This interpretation is consistent with the higher acoustic impedance values observed in the Well S-1 area, indicating denser, cleaner carbonate rocks with more favourable reservoir characteristics for hydrocarbon accumulation.

The results in Figure 13(d) show variations in Water saturation (S_w) along the southeast–northwest trend reveal contrasting reservoir conditions within the study area. The PNN model predicted a high average Water Saturation (S_w) of 0.9 (v/v) for Well T-1, whereas the average predicted Water Saturation for Well S-1 was 0.4 (v/v). Although both wells are dominated by limestone lithology, the difference in S_w values is attributed to stratigraphic geometry, specifically the development of carbonate stacking structures in the S-1 area that are absent in T-1. This interpretation is supported by the higher Acoustic Impedance (AI) values observed in Well S-1, which reflect differences in rock elastic properties between facies. Structurally, a northeast–southwest-trending fault is interpreted to have controlled hydrocarbon migration towards Well S-1. Therefore, the relatively low water saturation anomaly observed in S-1 suggests the presence of fluids other than formation water, most likely hydrocarbons, controlled by a

combination of stratigraphic and structural factors.

This interpretation is further supported by the Drill Stem Test (DST) results from Well S-1, which confirm the occurrence of biogenic gas within the study interval. The gas is predominantly composed of methane (98.95%), consistent with the characteristic composition of biogenic gas (PPPGL, 2018), as shown in Table 2.

Table 2. Gas Composition Results from the Drill Stem Test (DST) of Well S-1 (PPPGL, 2018).

Gas Composition	S-1 (Late Miocene)	
	Water Depth: 196 ft	
	DST 2 (%) 5198 – 5216 ft	DST 3 (%) 5034 – 5090 ft
Carbon Dioxide	0.29	0.23
Nitrogen	0.56	0.61
Ethane	0.18	0.19
Methane	98.95	98.96
Propane	0.02	0.01
Oxygen	0	0
Total	100	100

Conclusion

Based on the Probabilistic Neural Network (PNN) results, the estimated distribution of petrophysical properties within the carbonate reservoir of the Nias Basin demonstrates higher prediction accuracy than conventional multi-attribute analysis, particularly in reservoirs with complex heterogeneity. The PNN model achieved a correlation coefficient of 0.83 with a 10% error for Water Saturation (Sw), and a correlation coefficient of 0.88 with a 9% error for Carbonate Volume. The predicted distributions of Carbonate Volume and Water Saturation indicate that hydrocarbon accumulation is concentrated around Well S-1, which is characterized by high Carbonate Volume and resistivity, along with low Water Saturation. These results suggest that biogenic gas accumulation is localized around Well S-1, whereas the inferred hydrocarbon migration is controlled by the regional geological setting and the subsurface structural framework.

This study recommends incorporating the frequency-based attribute Amplitude Versus Frequency (AVF) as an external attribute, as its spectral sensitivity has the potential to improve the prediction of petrophysical properties in heterogeneous carbonate reservoirs when integrated with the Probabilistic Neural Network (PNN) approach.

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Author Contribution

The authors' contributions to this manuscript are as follows: **Chikita Mery Yuliani** and **Renita Dwi Vadila** contributed to conceptualization, formal analysis, and writing of the original draft. **Mokhammad Puput Erlangga** and **Harnanti Y. Hutami** were responsible for supervision, formal analysis, and validation. **Egie Wijaksono** contributed to the resources and data curation. All authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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