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Full Length Article

# Seismic attribute integration and neural network analysis for quantitative reservoir characterization: A case study from the Offshore Nile Delta (Egypt)

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A B S T R A C T

Accurate reservoir characterization is essential for optimizing hydrocarbon exploration and production, particularly in complex deep-water environments. The Simsat Field, Offshore Nile Delta, features a Pliocene deep-water turbidite reservoir, primarily composed of interbedded sand channels and shale, which poses significant challenges for reservoir delineation due to lateral lithological variations, limited well control, and complex stratigraphic architecture. Traditional seismic interpretation methods often struggle to capture the heterogeneity and connectivity of these reservoirs, leading to uncertainties in hydrocarbon prospect evaluation. To address these challenges, this study integrates seismic attributes, post-stack seismic inversion, and a multi-layer feed-forward neural network (MLFN) to enhance quantitative reservoir characterization. This integrated approach outperforms the limitations of individual techniques by combining the spatial resolution of seismic attributes, the lithology-fluid sensitivity of inversion, and the non-linear predictive capabilities of machine learning. The workflow provides a synergistic solution that improves property prediction accuracy and reduces interpretation uncertainty, particularly in data-limited, structurally complex settings. Spectral decomposition improves the visualization of channel morphology and stratigraphic variations, while seismic inversion generates acoustic impedance volumes that aid in lithology differentiation and fluid detection. The MLFN model, trained using well log data and multiple seismic attributes, provides high-accuracy predictions of shale volume (Vsh), porosity, and water saturation, significantly improving the assessment of reservoir quality. The results confirm a well-defined gas-bearing sandstone reservoir with high porosity (>18%) and low water saturation, indicating strong hydrocarbon potential. This integrated approach demonstrates the effectiveness of combining advanced seismic interpretation with machine learning techniques to reduce interpretation uncertainties, improve reservoir connectivity analysis, and optimize field development strategies in the West Delta Deep Marine (WDDM) concession. The findings provide valuable insights into reservoir heterogeneity and contribute to more effective hydrocarbon exploration and production in the Offshore Nile Delta.



## 1. Introduction

Reservoir characterization is a fundamental component of hydrocarbon exploration and production, providing a detailed understanding of subsurface properties that influence reservoir

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behavior, fluid distribution, and hydrocarbon potential (Gawad et al., 2019, 2020; Imam et al., 2022; Abdel-Fattah et al., 2023, 2024a; Reda et al., 2024a; Fathy et al., 2025a, 2025b). Over recent decades, advances in seismic acquisition and interpretation have enhanced our ability to delineate reservoirs; however, challenges persist—especially in deep-water settings—due to limited well control, complex depositional environments, and lateral lithological heterogeneity. Traditional seismic interpretation techniques often fail to resolve thin beds, identify stratigraphic discontinuities, or accurately predict petrophysical parameters (Alrefaee et al., 2018; Gawad et al., 2021a,b; Reda et al., 2025). These limitations hinder optimal field development and increase exploration risk. In response, the integration of seismic attributes and artificial intelligence (AI)-driven techniques, particularly neural networks, has emerged as a promising approach to enhance predictive accuracy by leveraging multi-source data (Hampson et al., 2001; Chopra and Marfurt, 2007a, b; Abdel-Fattah et al., 2020; Reda et al., 2022; Anwar et al., 2025; Sedki et al., 2025a; b). This approach represents a significant innovation by overcoming the limitations of traditional methods that rely on linear relationships and manual interpretation. The multi-layer feed-forward neural network (MLFN) model can capture complex, nonlinear interactions between seismic attributes and petrophysical properties, enabling more accurate prediction of lithology, porosity, and fluid saturation. Unlike conventional inversion or attribute analysis alone, the integrated workflow maximizes the predictive strength of each component: seismic attributes provide spatial variability, inversion offers impedance-based lithology discrimination, and machine learning enables data-driven calibration with well log data.

The Offshore Nile Delta is one of the most prolific hydrocarbon basins in the eastern Mediterranean (Fig. 1), with deep-water Pliocene–Pleistocene channelized sandstone reservoirs hosting significant gas accumulations (Weimer et al., 2000; Samuel et al., 2003; Abdel-Fattah and Slatt, 2013). These reservoirs are particularly challenging to characterize due to their complex architecture, marked by rapid facies changes, stratigraphic traps, and compartmentalization, which complicate hydrocarbon prediction and extraction (Bakr et al., 2023; Mamdouh et al., 2023, 2024; Mostafa et al., 2025; Shehata et al., 2023). The Simsat Field in the West Delta Deep Marine (WDDM) concession (Fig. 1) represents a complex deep-water turbidite system consisting of Pliocene sand channels interbedded with shale (Leila and Moscariello, 2019; Tyler and Finley, 1991; Weimer et al., 2000). Reservoir characterization in this field is challenging due to lateral lithological variations, limited well control, and the presence of intercalated shale layers that complicate seismic-based interpretations. To address these challenges, this study integrates seismic attributes, post-stack seismic inversion, and multi-layer feed-forward neural networks (MLFN) to enhance the quantitative characterization of the Simsat reservoir (Chopra and Marfurt, 2007a, 2007b; Hale, 2013; Marfurt and Alves, 2015; Iacopini et al., 2016; Di and Gao, 2017). Spectral decomposition techniques, including RGB color blending and frequency attribute analysis, are employed to delineate reservoir connectivity and stratigraphic features (Reda et al. 2024b, 2024c; Amir et al., 2025; Haddad et al., 2025). Seismic inversion is used to generate acoustic impedance volumes, aiding in lithology discrimination and fluid detection (El-Qalamoshy et al., 2023, 2024). The MLFN model leverages multiple seismic attributes and well log data to predict critical petrophysical properties such as shale content, porosity, and water saturation (Tingdahl and de Rooij, 2005; Smith and Treitel, 2010; Zheng et al., 2014a; Singh et al., 2016; Kumar, 2016).

This study aims to improve reservoir characterization by (1) defining reservoir morphology and stratigraphic connectivity using spectral decomposition, (2) estimating lithology and fluid content through post-stack seismic inversion, (3) applying a neural network-based approach to predict petrophysical properties, and (4) evaluating the effectiveness of integrating AI-driven models with seismic interpretation techniques. By leveraging these advanced methodologies, the study provides a more robust approach to hydrocarbon prospect evaluation and reserve estimation in deep-water channel reservoirs. The findings offer valuable insights into reservoir heterogeneity, contributing to more informed decision-making for exploration and development activities in the Offshore Nile Delta.

## 2. Field background

The Simsat Field is located in the West Delta Deep Marine (WDDM) concession, Offshore Nile Delta, approximately 125 km northeast of Alexandria, in a water depth of about 891 m (Fig. 1). It lies within one of the most prolific hydrocarbon provinces in the eastern Mediterranean. The field features a deep-water turbidite reservoir system, primarily composed of Pliocene sand channels interbedded with shale (Tyler and Finley, 1991; Weimer et al., 2000; Cohen et al., 2006). These sandstone reservoirs are characterized by excellent porosity and permeability, with hydrocarbons typically trapped beneath extensive regional shale seals, making them important targets for gas exploration and production (Leila

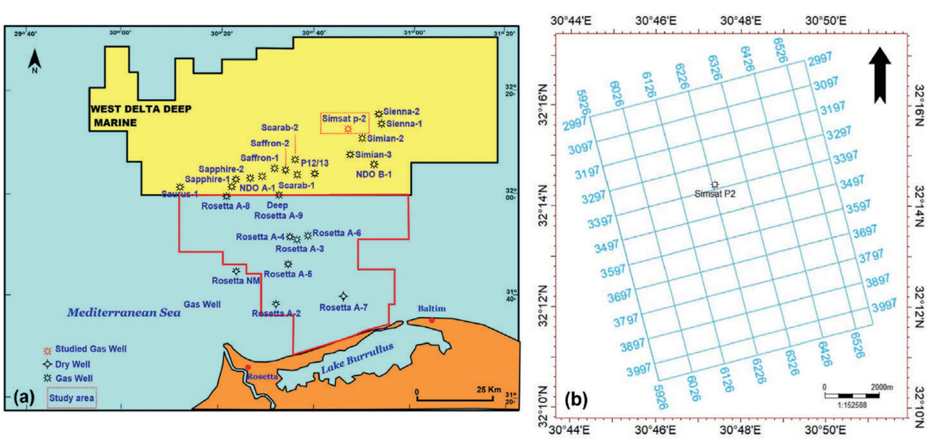


**Fig. 1.** (a) Location map of the West Delta Deep Marine (WDDM) concession, Offshore Nile Delta, showing existing wells and the position of Simsat P-2 within the study area. (b) Seismic survey grid covering the Simsat P-2 well, with inline and crossline numbers labeled. The grid represents the 3D seismic survey area used for reservoir characterization.

and Moscariello, 2019).

The stratigraphy of the study area is defined by a sequence of Pliocene–Pleistocene deposits, with the El Wastani Formation representing the main reservoir interval (Fig. 2). The formation consists of lowstand systems tracts deposited as basin-floor fans and channel-levee complexes, and it unconformably overlies the Kafr El Sheikh Formation. The reservoir architecture is complex, consisting of channelized sandstone bodies that vary laterally and vertically due to syn-depositional tectonics and sedimentary processes. These features, combined with the presence of intercalated shale layers and limited well control, pose significant challenges for traditional seismic-based reservoir characterization in the area.

Structurally, the field is influenced by the SW–NE-trending Nile Delta Offshore Anticline, which was likely active during Pliocene sediment deposition (Samuel, 2003). The interplay between structural elements and stratigraphy results in compartmentalized reservoirs, making it difficult to assess reservoir continuity and connectivity using conventional approaches. Therefore, advanced interpretation techniques and integrated workflows are essential to accurately delineate the reservoir geometry and estimate its hydrocarbon potential.

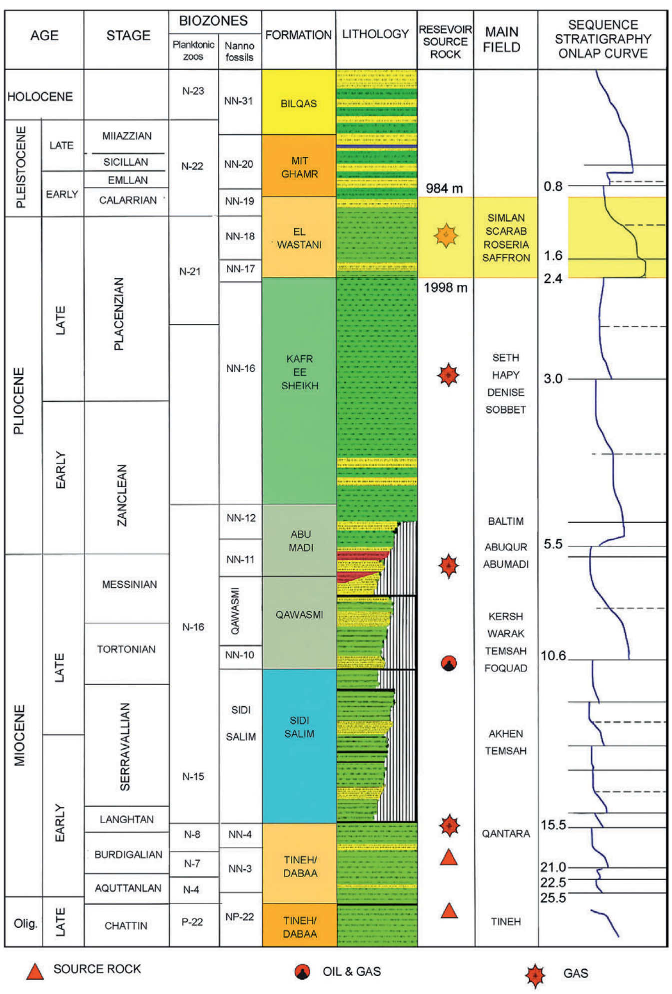


**Fig. 2.** Chronostratigraphic and lithostratigraphic framework of the West Delta Deep Marine (WDDM) concession, Offshore Nile Delta, showing key formations, lithologies, reservoirs, source rocks, seals, and tectono-stratigraphic events. Major gas fields and hydrocarbon discoveries are also highlighted (Leila and Moscariello, 2019). The formation under examination highlighted by the dashed red line.

## 3. Data and methods

This study utilizes 3D post-stack seismic data and well log data from the Simsat Field, located in the West Delta Deep Marine (WDDM) concession, Offshore Nile Delta. The seismic dataset spans 72 km$^2$, with 1071 inline profiles and 654 cross-lines, following SEG normal polarity standards. The well log dataset from the Simsat P2 well includes gamma-ray (GR), resistivity, sonic, neutron, and density logs.

Petrophysical evaluation of the Simsat P2 well involves interpreting well log responses to define lithology, porosity, and hydrocarbon saturation. The well logs are analyzed using cross-plot techniques, including neutron-density, neutron-sonic, and sonic-density cross-plots, which provide an integrated approach to lithological identification and reservoir quality assessment (Schlumberger, 1984; Abd Elhady et al., 2015; Abdel-Fattah et al., 2018; Hampson et al., 2001; Russell, 2002; Abdel-Fattah et al., 2024b). CPI logs are used to estimate shale volume, porosity, and water saturation, which aid in defining the net pay thickness and distinguishing hydrocarbon-bearing sands from surrounding shales. These well log analyses are crucial for establishing a calibrated reservoir model and validating seismic inversion results (Abdel-Fattah et al., 2025; Reda et al., 2024a).

Spectral decomposition techniques are applied to analyze frequency-dependent seismic attributes, which enhance the understanding of reservoir geometry and stratigraphic connectivity. For the reservoir characterization) used windowed spectral analysis to generate discrete-frequency energy cubes. Discrete Fourier Transform (DFT) and Continuous Wavelet Transform (CWT) are used for Spectral decomposition techniques to transform the seismic data into the frequency domain to have tuning cubes and a variety of discrete common frequency cubes. The red, green, blue (RGB color blending method) is commonly used in seismic interpretation and to delineate hydrocarbon distribution. By measuring the dominant frequency of the seismic data, and used the greatest and least overall seismic dominant frequency. The RGB color blending method, commonly used in seismic interpretation, is employed to visualize reservoir heterogeneity by combining low (5 Hz), mid (25 Hz), and high (50 Hz) frequency bands (Al-Dossary and Marfurt, 2006). This method provides a clearer distinction between high-energy sand-prone reservoirs and surrounding low-energy shale-rich deposits. Additional seismic attributes, including average absolute amplitude (AAA), energy attributes, instantaneous frequency, and amplitude-weighted phase, are extracted to improve reservoir identification and assess hydrocarbon potential (Elgendy et al., 2024). These attributes play a critical role in defining the morphology and lateral extent of reservoir compartments and improving the interpretation of depositional environments (Negm and Hammam, 2022).

Seismic inversion is performed to transform seismic reflection data into acoustic impedance (AI) volumes, which aid in distinguishing lithology and fluid content (Latimer et al., 2000; Veeken and Silva, 2002). In this study, the Model-based inversion technique was utilized to convert seismic amplitude to impedance value, and provide depth or time pictures of AI, which is considered one of the important parameters of rock physics. Mathematically, the seismic traces are generated by the convolution of a seismic wavelet with reflectivity, with some noise, as the following equation

$$s(t) = [w(t)*R(t)] + N(t) \tag{1}$$

where S(t) is seismic trace, W(t) represent the seismic wavelet, * the convolution operator, R(t) the reflectivity, * the and N(t) is the noise component of the data.

For a zero-offset seismic signal, the acoustic impedance of the underlying layer (Zi+1) can be calculated as follows:

$$Zi+1 = \mathrm{Zi}\left[\frac{1+Ri}{21-Ri}\right] \tag{2}$$

where $Ri$ represent P-wave reflection coefficient (zero offset) ith at the interface, and Z is the layer impedance, whereas $\mathrm{Zi} = \rho\mathrm{i} \times \mathrm{Vi}$, for the ith layer. where ρ is the density and V is the P-wave velocity

$$Zn = \mathrm{Zi}^{*}\pi\left[\frac{1+Ri}{21-Ri}\right] \tag{3}$$

By using equation (3), a seismic trace can effectively transform, or invert, the seismic reflection data to P-impedance. The inversion process follows a model-based approach, incorporating well log data and seismic attributes to improve subsurface characterization. The workflow includes wavelet extraction, initial model building, and Generalized Linear Inversion (GLI) (Hampson et al., 2001). The wavelet extraction process ensures an accurate well-to-seismic tie, allowing for better correlation between seismic reflectivity and subsurface lithology. An initial model is constructed by integrating well log data with seismic reflection information, providing constraints for inversion and improving the accuracy of impedance estimations. The GLI inversion process is then applied to iteratively refine impedance values, reducing errors and ensuring optimal agreement between synthetic and observed seismic data (Othman et al., 2018a). The final acoustic impedance volume serves as a key input for classifying lithology, estimating porosity, and differentiating hydrocarbon-bearing sands from shale-dominated intervals.

The neural network techniques in geophysics are applied to predict the reservoir characterization using a statistical or mathematical model based on data. The neural network is represented by two main categories, the first is a probabilistic neural network (PNN), and the second is the A multi-layer feed-forward neural network (MLFN). Based on Hampson et al. (2001), Neural Network (NN) learning algorithms proved notable validity and accuracy in predicting the reservoir characterization, and the multilayer feed-forward neural network (MLFN) is one of them.

A multi-layer feed-forward neural network (MLFN) is implemented to integrate seismic attributes and well log data for enhanced reservoir property estimation (Hampson and Russell, 2004). The network architecture consists of an input layer (seismic attributes), multiple hidden layers (processing nodes), and an output layer (predicted petrophysical properties). The model is trained using well log data, optimizing the weights of seismic attributes to minimize prediction errors (Heggland et al., 1999; Smith and Treitel, 2010). The selection of input attributes is based on their correlation with Vsh, porosity, and Sw, ensuring that the most relevant features are utilized for petrophysical predictions (Negm and Hammam, 2022). Mathematically, the input layers are multiplied by the (connection) weights; the results are represented by the weighted signals are summed and have a nonlinear function applied to them as follows:

$$y = f\left(\sum_{i=0}^{n=1} x_i w_i + w_n\right) \tag{4}$$

where y is the node output; $x_i$ is the node input; $w_i$ is the weight; $i = ¼, 1 \ldots n-1$; $w_n$ is a constant, and $f$ It is an activation function. by reducing the prediction error, the weights are optimized. A multi-layer feed-forward neural network (MLFN) utilizes integration conjugate-gradient analysis and simulated annealing to avoid trapping in the local minima and find the global minimum. The neural network undergoes iterative training and validation, using seismic attributes and well log data from Simsat P2 to establish relationships between seismic responses and reservoir properties. Once trained, the model is applied to the entire seismic volume, generating spatial distributions of Vsh, porosity, and Sw, which provide a detailed 3D petrophysical model (Reda et al., 2024b; Sarhan and Abdel-Fattah, 2024; Singh et al., 2016).

To predict porosity (Φ), shale volume (Vsh), and water saturation (Sw), a multi-layer feed-forward neural network (MLFN) was constructed using a supervised learning approach. The network was trained using seismic attributes—such as energy, inverted acoustic impedance (Zp), and amplitude-weighted phase—as input features, and the corresponding well log-derived petrophysical parameters as output targets. The general form of the neural network function can be expressed as:

$$\hat{y} = f\left(W^2 \cdot g\left(W^1 \cdot x + b^1\right) + b^2\right) \tag{5}$$

Where:

x is the input vector of seismic attributes, $W^1$ and $W^2$ are the weight matrices for the first and second layers, $b^1$ and $b^2$ are the bias vectors, g(·) is the activation function for the hidden layer (ReLU or sigmoid), f(·) is the output activation function (linear),

ŷ is the predicted petrophysical property (Φ, Vsh, or Sw).

The model was trained to minimize the mean squared error (MSE) loss function:

$$\mathrm{MSE} = (1 / n) \sum (y_i - \hat{y}_i)^2 \tag{6}$$

Where $y_i$ is the actual log-derived value and $\hat{y}_i$ is the predicted output. The optimization was performed using a conjugate-gradient algorithm with simulated annealing to avoid local minima (Smith and Treitel, 2010). The model's predictive performance was validated using correlation coefficients (R) and average absolute errors between predicted and actual log values (Hampson et al., 2001; Singh et al., 2016; Zheng et al., 2014a, b). The use of multiple seismic attributes as input enhances the network's ability to capture nonlinear relationships between seismic signals and rock properties (Tingdahl and de Rooij, 2005).

The neural network model developed in this study was designed to perform regression tasks for predicting continuous reservoir properties—specifically porosity, shale volume (Vshale), and water saturation—rather than classification. The multi-layer feed-forward neural network (MLFN) was trained using seismic attributes as input features and well log-derived petrophysical parameters as target outputs. During training, the model learned the complex, non-linear relationships between seismic data and reservoir properties. The importance of each input attribute was evaluated based on its contribution to the predictive accuracy of the model. Once trained, the model was applied across the entire seismic volume to generate continuous 3D distributions of the predicted petrophysical parameters. These outputs reflect spatial variations in reservoir quality and fluid content, enabling a detailed quantitative interpretation of the subsurface.

This integrated workflow, combining well log analysis, spectral decomposition, seismic inversion, and machine learning techniques, provides a comprehensive approach to reservoir characterization. The study enhances the understanding of reservoir architecture, improves lithology differentiation, helps to identify the channel fairways and delineate the channel continuity, and refines hydrocarbon prospectivity assessments, contributing to more effective exploration and production strategies in the Offshore Nile Delta.

## 4. Results

### 4.1. Well log analysis for simsat P2

The well log analysis of the Simsat P2 well provided crucial insights into lithology, reservoir quality, and fluid distribution within the study area. The gamma-ray (GR) log indicated a dominant sandstone lithology, with low GR values confirming clean, hydrocarbon-bearing sand intervals and higher GR values marking interbedded shale layers. The resistivity logs showed distinct high-resistivity zones, correlating with gas-bearing sands, while lower resistivity values suggested water-saturated or shaly formations (Gawad et al., 2021a,b). Cross-plot analysis of neutron-density relationships further validated the lithological composition, distinguishing clean sandstone reservoir (Fig. 3). The neutron-density cross-plot confirmed the presence of a high-porosity sandstone reservoir, as indicated by low neutron and density readings, characteristic of gas-filled formations.

The CPI (Computer Processed Interpretation) results revealed a net pay thickness of approximately 13.9 m, with an effective porosity of ~13% and shale content (Vsh) below 15% (Fig. 4). The water saturation (Sw) analysis showed low values in the main reservoir zone, confirming the presence of hydrocarbons, with Sw reaching as low as 48%, leading to a calculated hydrocarbon saturation of 52%. The lateral and vertical distribution of reservoir properties suggests that the sandstone channel exhibits good reservoir potential, with adequate porosity and low shale content, supporting favorable reservoir connectivity and hydrocarbon storage. The integration of these well log interpretations with seismic data further enhances reservoir delineation and hydrocarbon prospectivity assessments in the Simsat Field.

### 4.2. Spectral decomposition and seismic attribute analysis

The spectral decomposition and seismic attribute analysis provided a detailed understanding of the reservoir geometry, stratigraphic variations, and lithological distribution in the Simsat Field. The spectral decomposition results highlight distinct channelized reservoir systems in the Simsat P-2 well area, with the upper and lower channel clearly delineated by high-energy amplitude contrasts (Fig. 5). The time-slice and seismic cross-sections reveal that these channels are laterally extensive, with well-defined high-amplitude anomalies, indicating potential hydrocarbon-bearing sand deposits. The seismic cube at the Simsat Field reveals high-amplitude anomalies (Fig. 6a), indicating potential reservoir channels and stratigraphic variations. The time-frequency spectrum panel for the full-stack seismic data (2176–2520 ms) highlights amplitude variations that suggest changes in lithology and fluid content, supporting the identification of hydrocarbon-bearing intervals within the study area (Fig. 6b).

The RGB color blending technique, using 5 Hz (red), 25 Hz (green), and 50 Hz (blue) frequency bands, effectively delineated the reservoir morphology and stratigraphic connectivity (Fig. 7). The results revealed that the reservoir channel system is composed of two main compartments, oriented NW-SE and NE-SW, with a low-energy tuning zone separating them. This tuning zone suggests potential lateral variations in lithology and fluid content, which could influence reservoir connectivity and production efficiency. The selected frequency bands were chosen based on the dominant frequency content of the seismic data and the expected vertical resolution relative to the reservoir thickness. Lower frequencies (e.g., 5 Hz) capture large-scale stratigraphic features, while higher frequencies (e.g., 50 Hz) enhance resolution of thinner beds and finer details. The 25 Hz mid-range frequency serves to balance vertical detail and continuity. This combination ensures effective visualization of channel boundaries, internal heterogeneity, and stratigraphic discontinuities in relation to the average reservoir thickness observed from well log data.

The average absolute amplitude (AAA) and instantaneous frequency attributes further supported the identification of high-energy reservoir facies, indicating areas of potential hydrocarbon accumulation (Fig. 8). The high-amplitude anomalies observed in the spectral decomposition analysis correspond to gas-charged sandstone intervals, whereas the low-amplitude regions are associated with shale-dominated zones. The amplitude-weighted phase attribute helped in distinguishing thin-bed interference effects, providing additional confirmation of sand-body continuity and depositional patterns.

The combined results from spectral decomposition and seismic attribute analysis suggest that the hydrocarbon-bearing sands in the Simsat Field are well-defined, laterally continuous, and exhibit favorable reservoir properties (Figs. 5–8). The spatial distribution of attributes indicates potential stratigraphic traps, highlighting areas with high reservoir quality. These findings enhance the understanding of subsurface heterogeneity, supporting improved reservoir characterization and hydrocarbon prospect evaluation in the West Delta Deep Marine (WDDM) concession, Offshore Nile Delta.

### 4.3. Post-stack seismic inversion

The post-stack seismic inversion successfully transformed seismic reflection data into acoustic impedance (AI) volumes, providing a quantitative assessment of reservoir lithology, porosity, and fluid properties in the Simsat Field. The inversion process converted the seismic data from interface properties to layered properties, enabling a more accurate representation of subsurface characteristics (Veeken et al., 2002). Acoustic impedance, which is derived from rock density and P-wave velocity, was used to predict reservoir zones, identify hydrocarbon-bearing intervals, and differentiate lithologies (Othman et al., 2014; Negm and Hammam, 2022).

The first step in the inversion workflow was the well-to-seismic tie, which ensured the correct detection of seismic horizons. A statistical wavelet extraction was performed, utilizing auto-

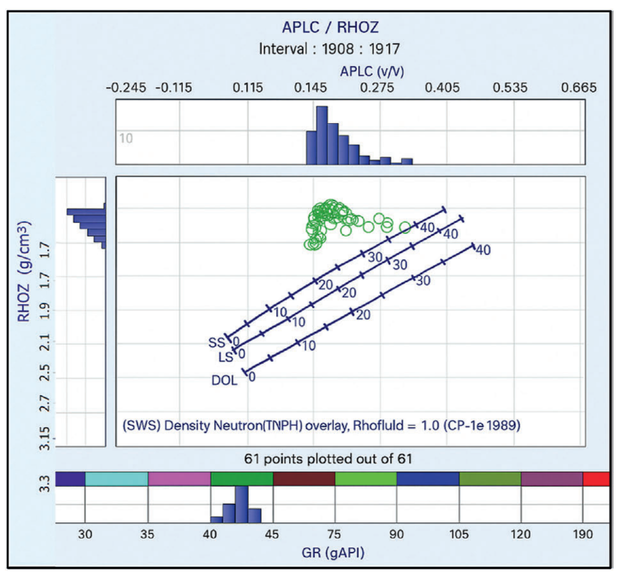


**Fig. 3.** Neutron-Density Crossplot showing sandstone lithology with low shale content, high porosity, and potential gas-bearing reservoir in the Simsat P-2 well.

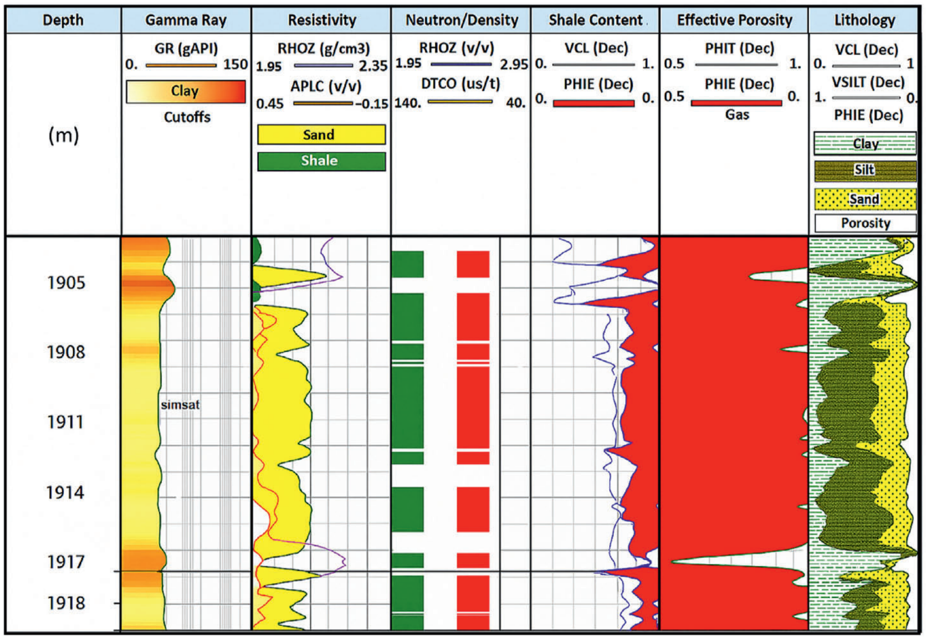


**Fig. 4.** Petrophysical log analysis highlighting gas sandstone reservoir with high effective porosity and low water saturation in the Simsat P-2 well.

correlation with a taper length of 25, a wavelength of 200, an offset of 0, a frequency smoother of 10 Hz, and a time window from 2150 to 2550 ms (Fig. 9). The seismic-synthetic correlation analysis at the Simsat P2 well showed high correlations, confirming the accuracy of the wavelet extraction process (Fig. 10). The initial model for inversion was generated by integrating well-log data with stacked seismic data, which provided constraints for the inversion and ensured that the results remained geologically plausible. The Generalized Linear Inversion (GLI) algorithm was then applied, iteratively modifying the model to minimize misfit and achieve optimal agreement between seismic-derived and observed impedance values.

The seismic inversion results demonstrated a strong correlation (99%) with the original well log data, with a minimal error of 0.12%, validating the accuracy of the inversion outputs (Fig. 11). The P-impedance volumes, which integrate both low and high frequencies from well data and seismic reflection, revealed significant variations in lithology and fluid content. The interpretation of impedance values enabled the differentiation between high-density, low-porosity formations and low-density, high-porosity sands, which are more favorable for hydrocarbon accumulation.

The rock physics cross-plots were employed to define impedance cut-offs and distinguish between various lithologies and fluid types (Fig. 12). These cross-plots analyzed relationships such as velocity vs. porosity and impedance vs. saturation, further refining the classification of reservoir facies. Based on these results, a 3D facies cube was generated, classifying the subsurface into three distinct units:

- Facies Sand (yellow) – Representing high reservoir potential, with favorable porosity and hydrocarbon saturation.

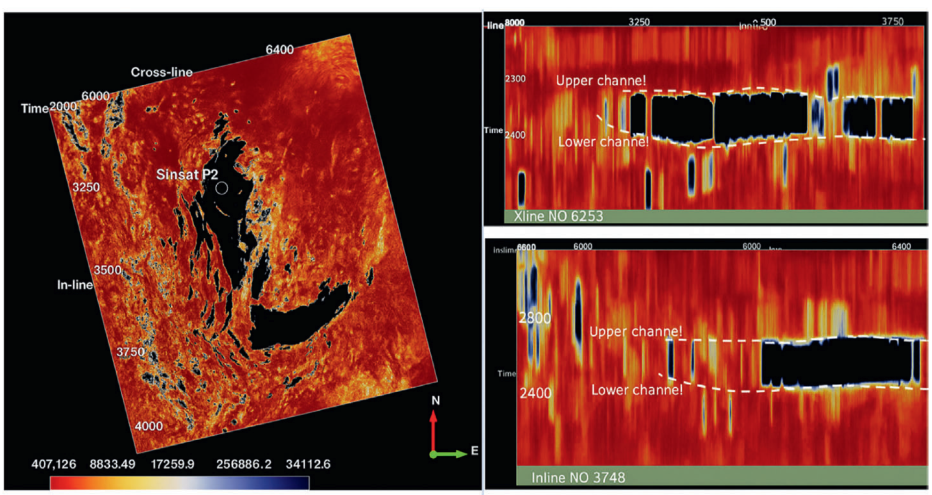


**Fig. 5.** Time slice and cross sections highlighting the reservoir channel dominated by high energy indicated by black color where the surrounding is dominated by low energy indicated by yellow color.

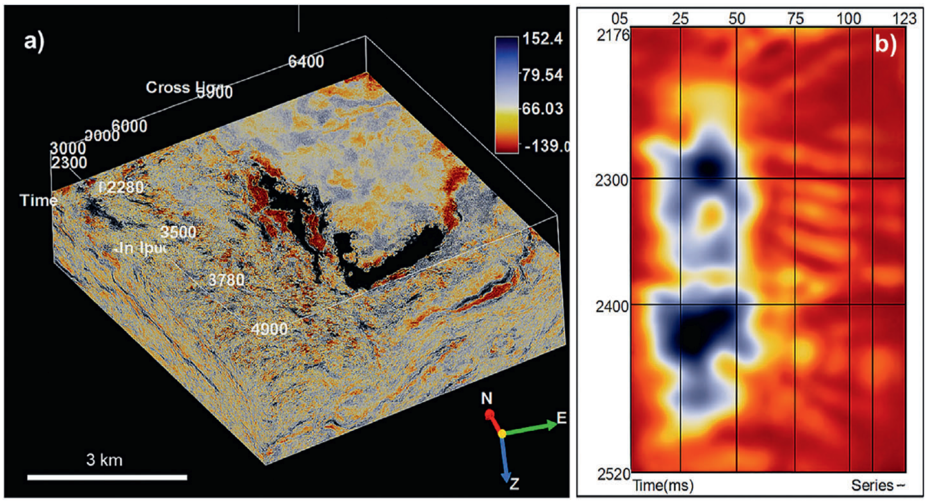


**Fig. 6.** (a) three-dimensional Seismic cube at Simsat field, (b) time frequency spectrum panel amplitude spectrum for the full stack seismic data within the interval 2176–2520 ms.

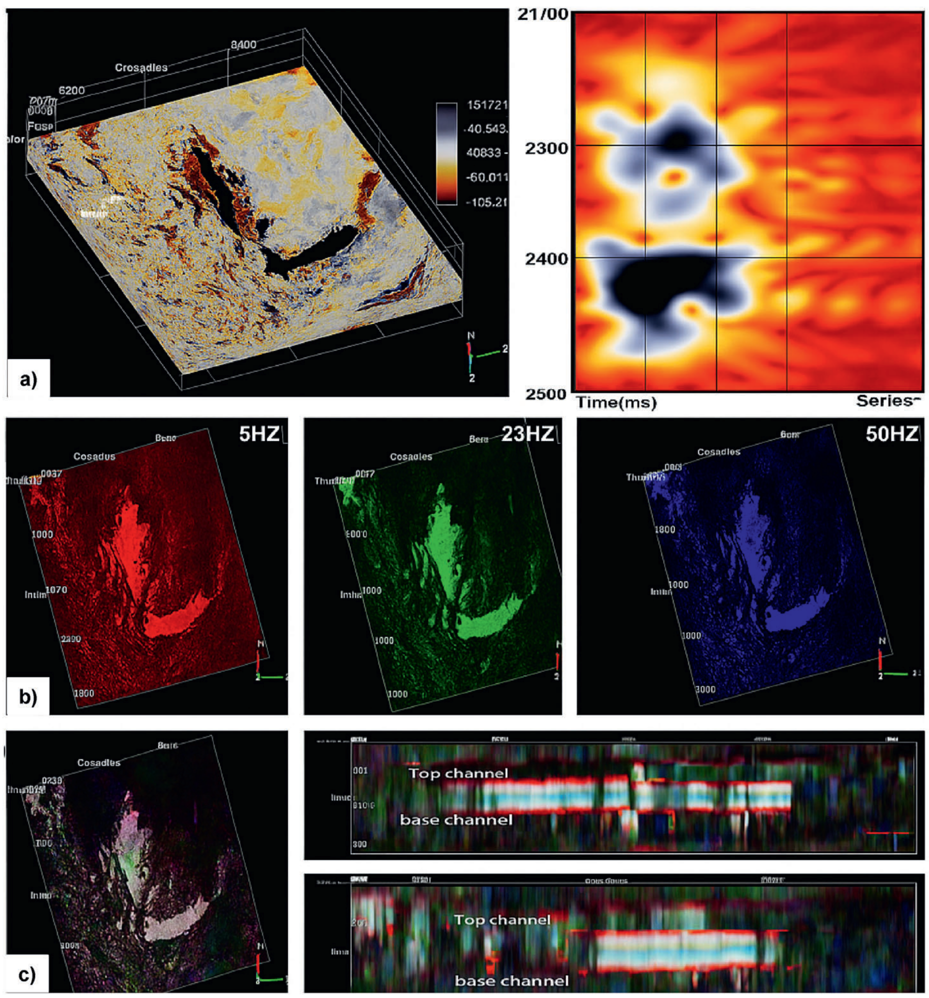


**Fig. 7.** Spectral decomposition results illustrating the geomorphological features of the reservoir channel system. a) Time slice and vertical section showing seismic amplitude anomalies corresponding to the interpreted channel complex. b) Frequency slices at 5 Hz, 25 Hz, and 50 Hz revealing different aspects of the channel morphology—low frequency highlights broader features, while higher frequencies enhance thin-bed details. c) RGB blended volumes combining 5 Hz (red), 25 Hz (green), and 50 Hz (blue) attributes to delineate the top and base of the channel system with improved clarity and stratigraphic contrast.

- Shaly Sand (blue) – Transitional zones with mixed lithology and lower porosity.
- Background Shale (red) – Non-reservoir zones with high clay content and poor porosity.

An arbitrary seismic line passing through the Simsat P2 well was extracted from the facies cube, providing a spatial representation of facies distribution across the study area (Fig. 13). This visualization highlighted the lateral extent of the sandstone reservoir, showing clear differentiation between reservoir-quality sands, shaly transition zones, and background shale. The juxtaposition of these facies helped refine reservoir boundaries, improve depositional environment interpretations, and enhance hydrocarbon exploration strategies. The seismic inversion results provided a high-resolution subsurface model, offering a reliable representation of reservoir architecture and hydrocarbon distribution (Fig. 13). The strong correlation with well log data, combined with the integration of rock physics and facies classification, validated the robustness of the inversion workflow. This study underscores the importance of seismic inversion and rock physics in characterizing reservoir properties, ensuring a detailed understanding of subsurface heterogeneity, and guiding hydrocarbon prospect identification in the Simsat Field, Offshore Nile Delta.

### 4.4. Neural network modeling for petrophysical prediction

The multi-layer feed-forward neural network (MLFN) model was applied to predict shale volume (Vsh), porosity (φ), and water saturation (Sw) by integrating seismic attributes with well log data. A wide range of seismic attributes was analyzed to identify the most influential parameters for reservoir property estimation (Fig. 14). The selected seismic attributes included energy, seismic time, filter 10/50/20, amplitude-weighted phase, dominant frequency, and instantaneous phase, identified through multi-attribute regression analysis (Hampson and Russell, 2004). Among these, energy exhibited the highest influence, followed by inverted acoustic impedance (Zp) and amplitude-weighted phase, ensuring the best attribute combination for input to the neural network.

The training phase of the MLFN model aimed to optimize the weighting of seismic attributes to minimize prediction errors and

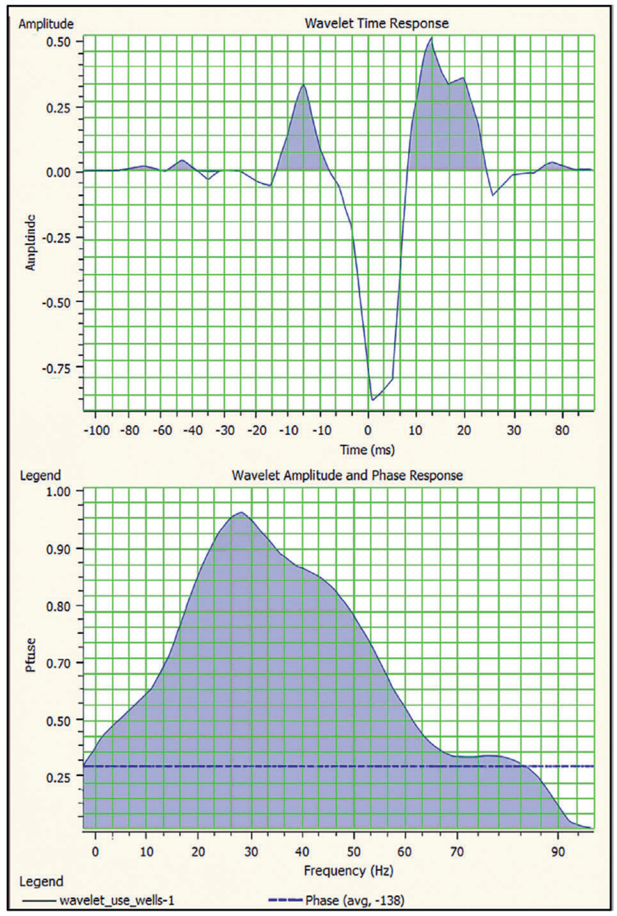


**Fig. 9.** Statistical wavelets for a full stack, with time response on top and respective amplitude spectrum on the bottom.

maximize correlation with well-log petrophysical properties (Fig. 15). The network architecture included an input layer with seven seismic attributes, a hidden layer with six nodes, and an output layer predicting two petrophysical properties. The training

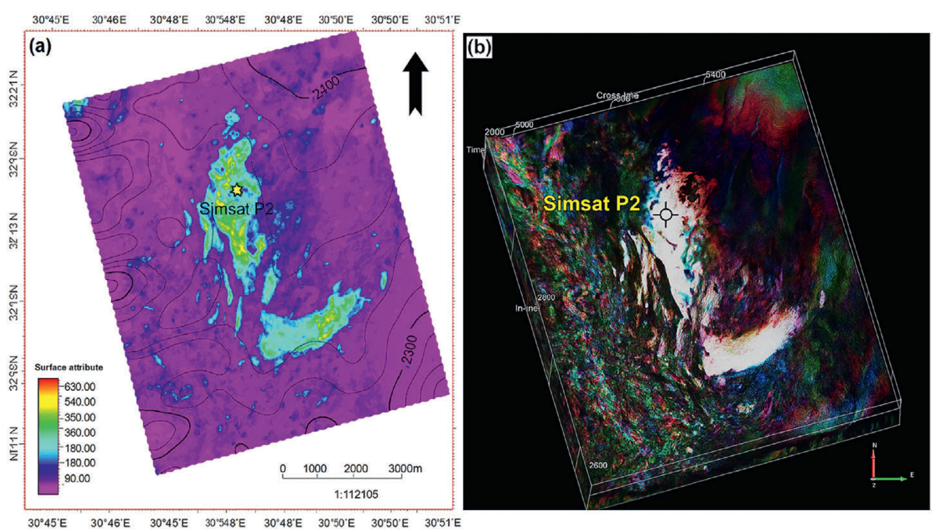


**Fig. 8.** a) Average magnitude (AAA) attribute map highlighting the reservoir channel geometry. b) RGB color-blended spectral decomposition of three frequencies showing enhanced delineation of the channel system around Simsat P2.

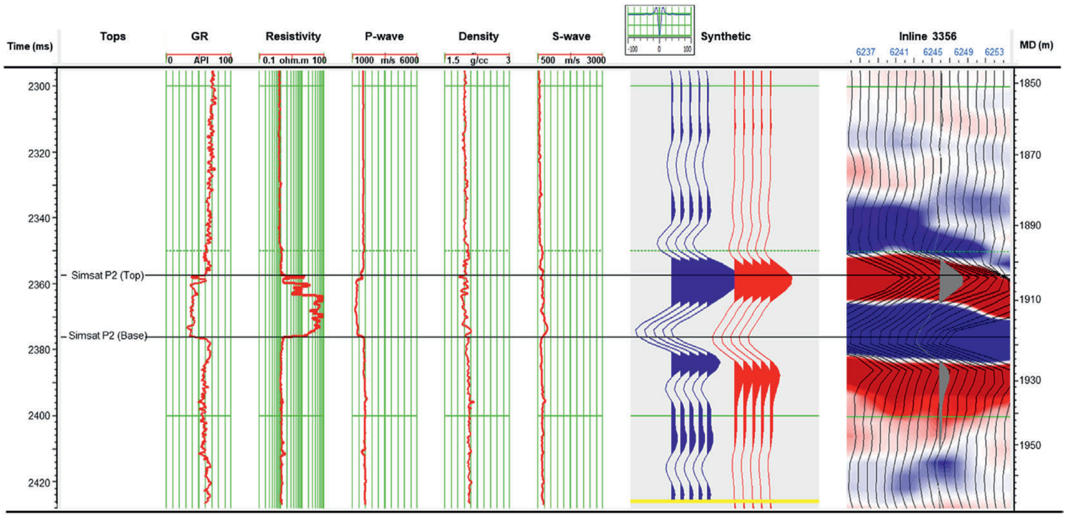


**Fig. 10.** Well ties in Simsat P2 well. The logs (from left to right) are, GR, Resistivity, P-wave, Density and S-wave. The blue seismic trace is the calculated synthetic, and the red is the real seismic data respectively, using the previous statistical wavelet.

process underwent multiple iterations to fine-tune the model, adjusting attribute weights until a maximum correlation and minimum error between the predicted network result and the known well log data were achieved. The final trained network delivered high correlation coefficients of 0.95 for porosity, 0.93 for water saturation, and 0.91 for shale volume, with minimal prediction errors of 0.10, 0.11, and 0.31, respectively (Figs. 16 and 17).

Following successful training, the MLFN model was applied across the entire seismic volume to generate 3D petrophysical property volumes for porosity, shale volume, and water saturation. The porosity volume revealed high-porosity zones (≥18%), concentrated within sandstone formations, indicating favorable reservoir quality. The shale volume (Vsh) prediction confirmed that the reservoir is dominated by low shale content (≤40%), reinforcing the presence of clean reservoir sands. The water saturation (Sw) distribution demonstrated low saturation values in high-porosity, low-shale-content zones, further supporting the hydrocarbon-bearing potential of the reservoir.

The vertical seismic sections of shale volume across the Simsat P2 well revealed distinct facies separation, categorizing the subsurface into three main lithological groups (Fig. 18):

- Low shale content (32–40%) – Corresponding to high-quality sandstone reservoirs with high porosity (≥18%), indicating optimal hydrocarbon storage.
- Intermediate shale content (40–60%) – Representing shaly sand facies, characterized by moderate porosity (11–14%) and acting as transitional zones.
- High shale content (>60%) – Associated with background shale facies, exhibiting low porosity (<10%) and poor reservoir quality.

The water saturation analysis, in correlation with shale content and porosity, confirmed that the reservoir is dominated by low-water-saturation zones, reinforcing the high-quality reservoir characteristics. A spatial analysis of MLFN-derived petrophysical

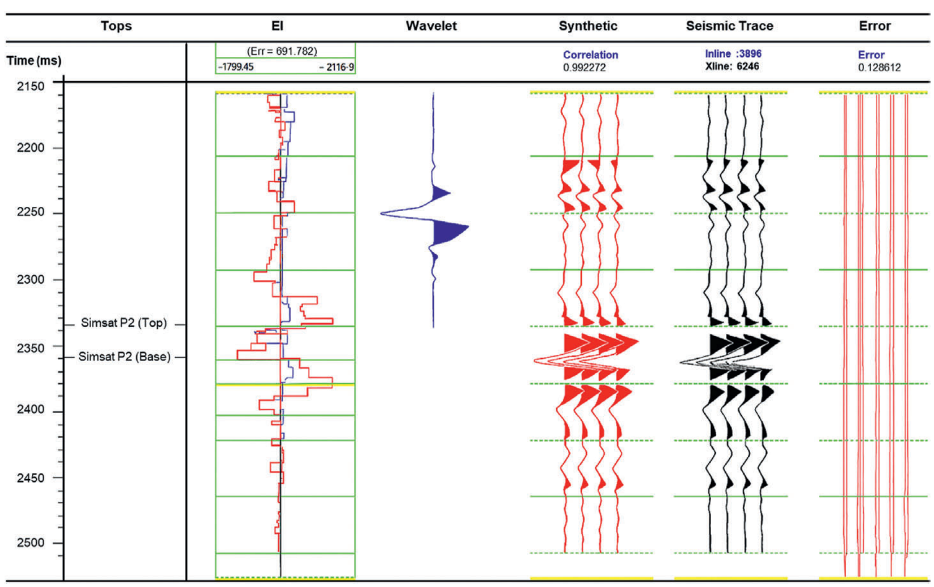


**Fig. 11.** Post-stack inversion analysis for Simsat P2 using well deterministic wavelet. The logs From Left to Right the columns shown on the bottom of the figure.

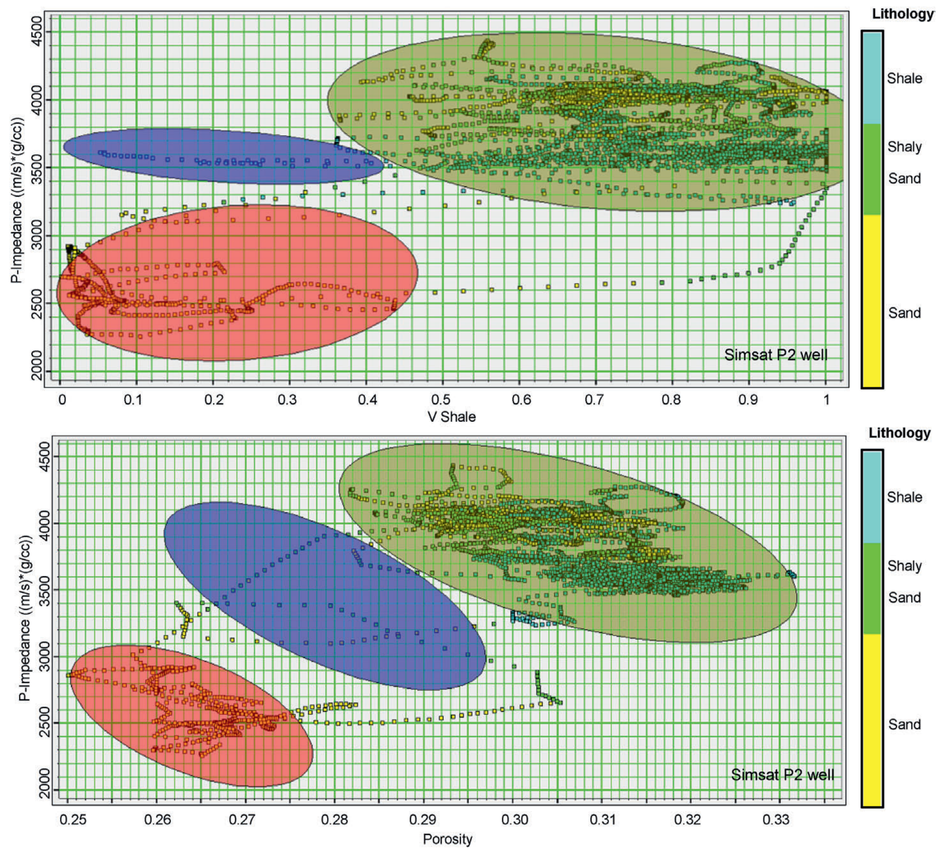


**Fig. 12.** Vshale and porosity ratio versus P-impedance crossplot color coded by lithology obtained from simsat P2 well.

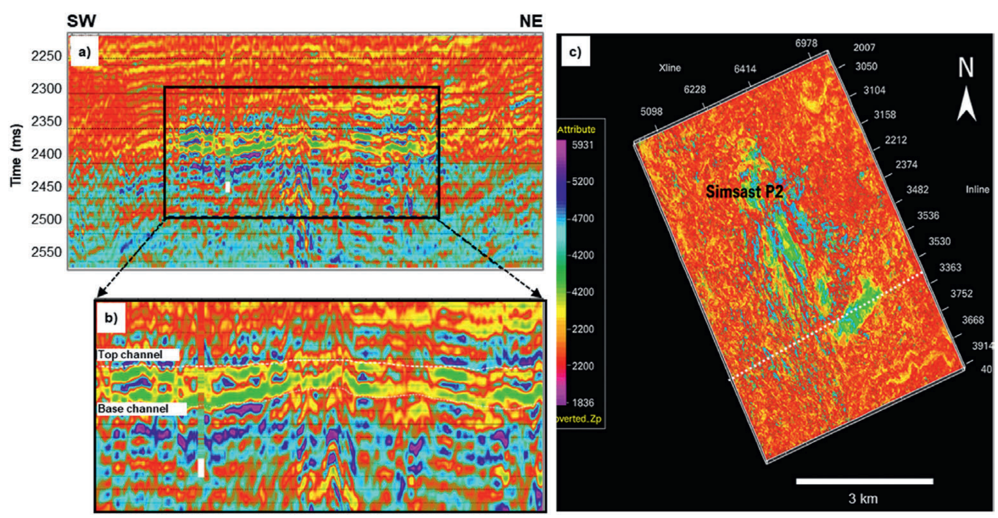


**Fig. 13.** (a) Cross-section of the Model-Based inversion results along the reservoir channel. The map shows the arbitrary line through the channel. (b) A clear inversion separation appears along Simsat P2 well location. (c) time slice extraction over the channel Note that the dominant color is the dark green which refers to gas sand.

property slices across the reservoir interval highlighted key hydrocarbon-bearing zones, distinguished by low shale content, low water saturation, and high porosity (Fig. 19). These findings significantly enhance reservoir characterization and development planning, providing valuable insights into reservoir heterogeneity, connectivity, and production potential in the Simsat Field, West Delta Deep Marine (WDDM) concession, Offshore Nile Delta. The MLFN model achieved strong predictive performance, with correlation coefficients (R) of 0.92 for shale volume, 0.95 for porosity, and 0.95 for water saturation (Figs. 17 and 19). These values confirm a high statistical agreement between predicted and actual well log-derived properties.

## 5. Discussion

The integration of seismic inversion and spectral decomposition significantly improved the reservoir characterization of the Simsat Field, Offshore Nile Delta. The spectral decomposition results revealed distinct high-energy depositional features, corresponding to potential hydrocarbon-bearing sand bodies (Figs. 5 and 6). The RGB color blending technique effectively delineated reservoir geometry and stratigraphic variations, confirming the presence of channelized sand reservoirs with lateral continuity and connectivity (Othman et al., 2014; Othman et al., 2018b; Negm and Hammam, 2022). Post-stack seismic inversion further enhanced the interpretation by converting seismic reflection data into acoustic impedance (AI) volumes, which provided valuable insights into lithology differentiation and fluid content (Fig. 11). The strong correlation between inversion results and well log data validated the ability of seismic inversion to accurately distinguish high-porosity, gas-bearing sandstone reservoirs from surrounding shale formations, reducing uncertainties in hydrocarbon prospect evaluation (Negm and Hammam, 2022). The model-based inversion method was selected over other techniques such as sparse-spike or band-limited inversion due to its ability to incorporate well-derived low-frequency trends and maintain geological plausibility. This approach is particularly effective in the Simsat Field, where maintaining stratigraphic continuity and honoring impedance contrasts is essential for accurate reservoir delineation.

A comparative assessment between the original seismic data (Fig. 5), the inverted acoustic impedance (AI) volume (Fig. 11), and the final predicted petrophysical properties (Fig. 18) provides valuable insights into the effectiveness of the integrated workflow. The original seismic amplitude data offered general structural and stratigraphic information but lacked the resolution needed to directly infer rock and fluid properties. The model-based inversion significantly improved vertical resolution and lithological contrast by transforming seismic reflections into quantitative AI volumes, which better correlate with rock properties such as porosity and lithofacies. Building on this, the MLFN model used seismic attributes—including AI—as inputs to generate high-resolution 3D volumes of porosity, Vshale, and water saturation. These predicted outputs show improved lateral and vertical continuity compared to the original seismic data and provide more direct and interpretable indications of reservoir quality. This stepwise enhancement from raw seismic (Fig. 5) to AI (Fig. 11) to predicted petrophysical properties (Fig. 18) demonstrates the added value of the integrated approach for reservoir characterization.

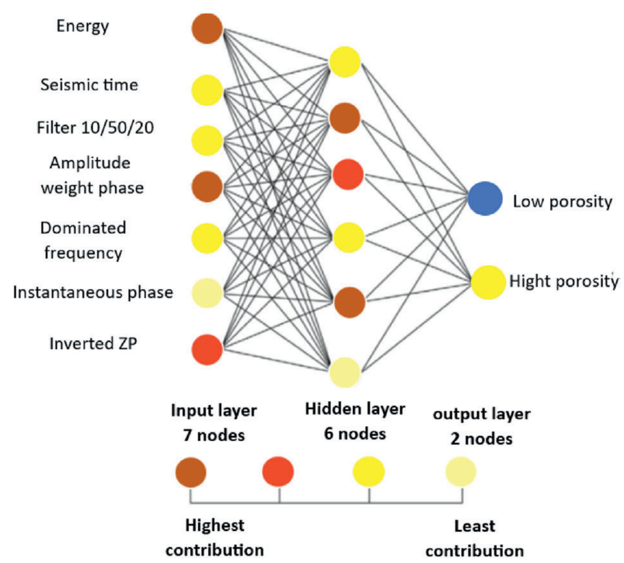


**Fig. 15.** The multi-layer feed-forward neural network (MLFN) used for this study consists of an input layer, an output layer, and one or more hidden layers. Each layer consists a set of nodes, called processing units. The relative contribution or weights of each input node are represented by color scale from brown to yellow. the high contribution indicated by brown color for the porosity.

The application of machine learning techniques provided further improvements in predicting reservoir properties beyond well control (Tingdahl and de Groot, 2003; Tingdahl and de Rooij, 2005; Smith and Treitel, 2010; Zheng et al., 2014a,b; Singh et al., 2016; Kumar, 2016). The multi-layer feed-forward neural network (MLFN) model successfully integrated seismic attributes with well log data, producing high-accuracy predictions for porosity, shale volume, and water saturation. The model's correlation coefficients of 0.95 for porosity, 0.93 for water saturation, and 0.92 for shale volume confirm its reliability in reservoir property estimation (Figs. 15 and 16). The contributions of seismic attributes such as energy, amplitude-weighted phase, and inverted acoustic impedance (Zp) were crucial in refining the spatial

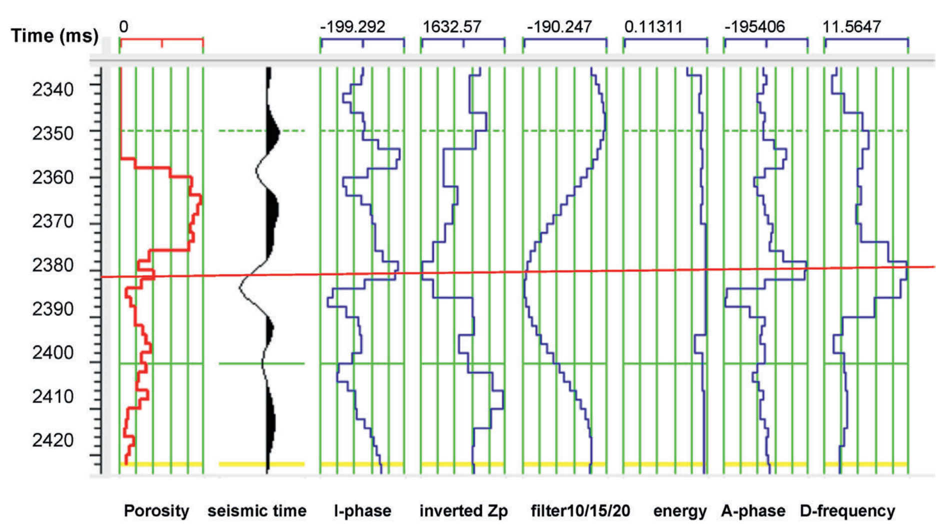


**Fig. 14.** Porosity log for Simsat P2 well versus seismic attributes, the red lines are showing the reservoir zone.

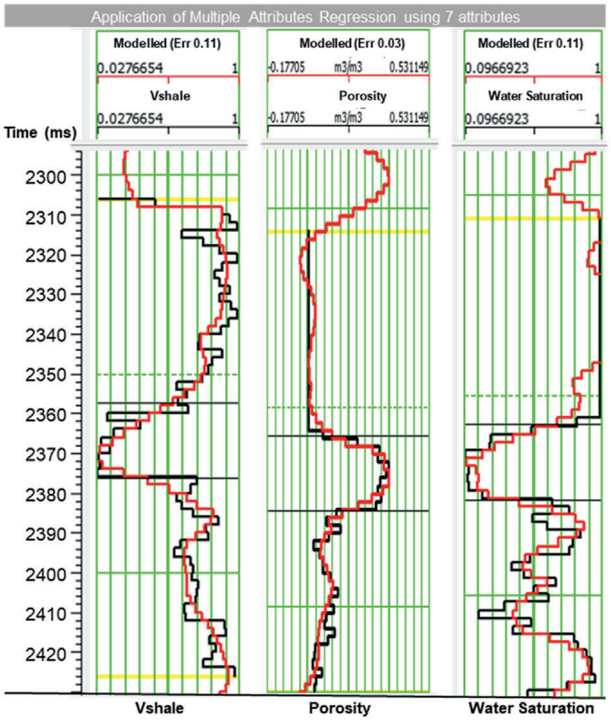


**Fig. 16.** The application of the Multi-Layer Feed Forward Neural Network. Measured logs Vshale, porosity and Water saturation (in black) and the predicted logs (in red) using Simsat P2 wells in the training. The normalized correlation coefficient for V Shale is 0.92, water saturation 0.93 and the porosity 0.93.

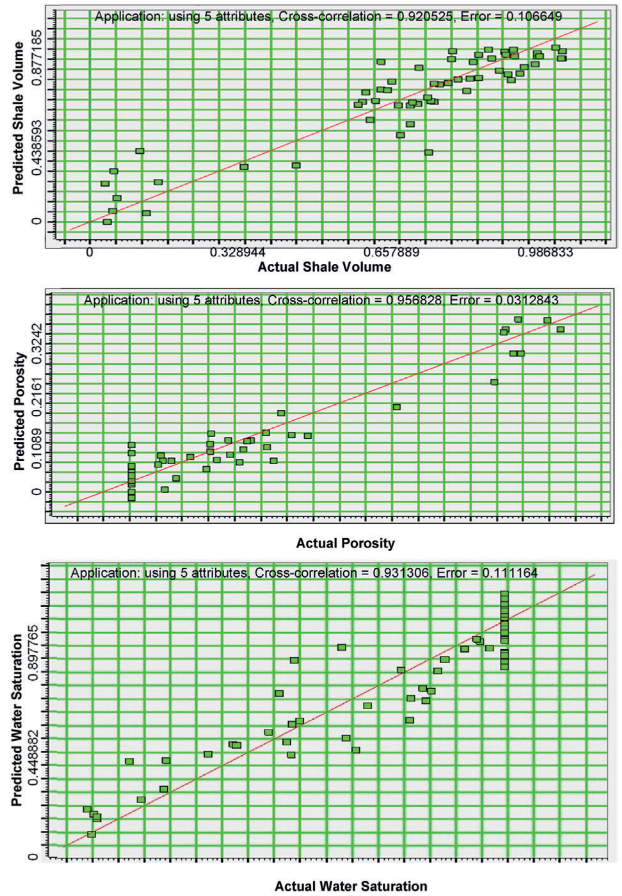


**Fig. 17.** Cross plots showing Actual Versus Predicted logs of Vshale, porosity and Water saturation which resulted from MLFN with correlation 0.92, 0.95 and 0.95 respectively.

distribution of petrophysical properties (Table 1). The ability to generate 3D petrophysical property volumes provided a more detailed understanding of reservoir quality, hydrocarbon distribution, and structural heterogeneity, supporting improved reservoir modeling and field development planning (Reda et al., 2024b). Unlike previous studies that apply seismic inversion or machine learning independently, our approach uniquely integrates inversion results, frequency-based attributes, and neural network prediction into a unified workflow tailored to deep-water turbidite systems. This integration enables enhanced prediction accuracy and greater resolution of lithological and fluid variations across the reservoir. While earlier works (e.g., Chen et al., 2022, 2024; Hampson et al., 2001; Singh et al., 2016) demonstrate the potential of AI models for property prediction, this study extends their applicability by calibrating machine learning with frequency-specific seismic responses and inversion-derived rock properties, addressing interpretation gaps in data-scarce environments.

The integration of seismic inversion, spectral decomposition, and neural network modeling confirmed the presence of laterally extensive, high-quality sandstone reservoirs with favorable porosity and fluid content. The post-stack inversion results clearly distinguished between reservoir facies, with low-impedance zones corresponding to hydrocarbon-bearing sands (Fig. 13). The MLFN-derived porosity and water saturation volumes further validated the findings, revealing low shale content ($\leq$15%) and hydrocarbon saturation of ~52%, making these reservoirs viable hydrocarbon targets (Figs. 17 and 18). The interpretation of these results suggests that the Simsat Field reservoirs exhibit good reservoir connectivity, essential for sustaining hydrocarbon production. These results emphasize the value of integrating AI-driven predictive modeling with advanced seismic interpretation techniques for improved reservoir characterization and hydrocarbon prospect evaluation. The ability to predict reservoir properties with high accuracy ensures better well placement, production optimization, and risk reduction in deep-water hydrocarbon plays (Singh et al., 2016; Reda et al., 2024b). The study demonstrates that machine learning, when combined with seismic inversion and attribute analysis, is an effective tool for subsurface reservoir characterization. This research contributes a practical, scalable methodology for deep-water reservoirs, particularly where well data is limited, bridging the gap between advanced computational tools and geologic interpretation. The findings provide a reliable basis for field development strategies, supporting informed decision-making in the West Delta Deep Marine (WDDM) concession, Offshore Nile Delta. Future work should explore additional geophysical parameters and machine learning refinements to further improve the accuracy of hydrocarbon prospect evaluation.

While the primary focus of this study was on developing an integrated reservoir characterization workflow, a brief assessment of uncertainty was conducted through correlation analysis and prediction error evaluation. The multi-layer feed-forward neural network (MLFN) model achieved high correlation coefficients—0.95 for porosity, 0.93 for water saturation, and 0.91 for

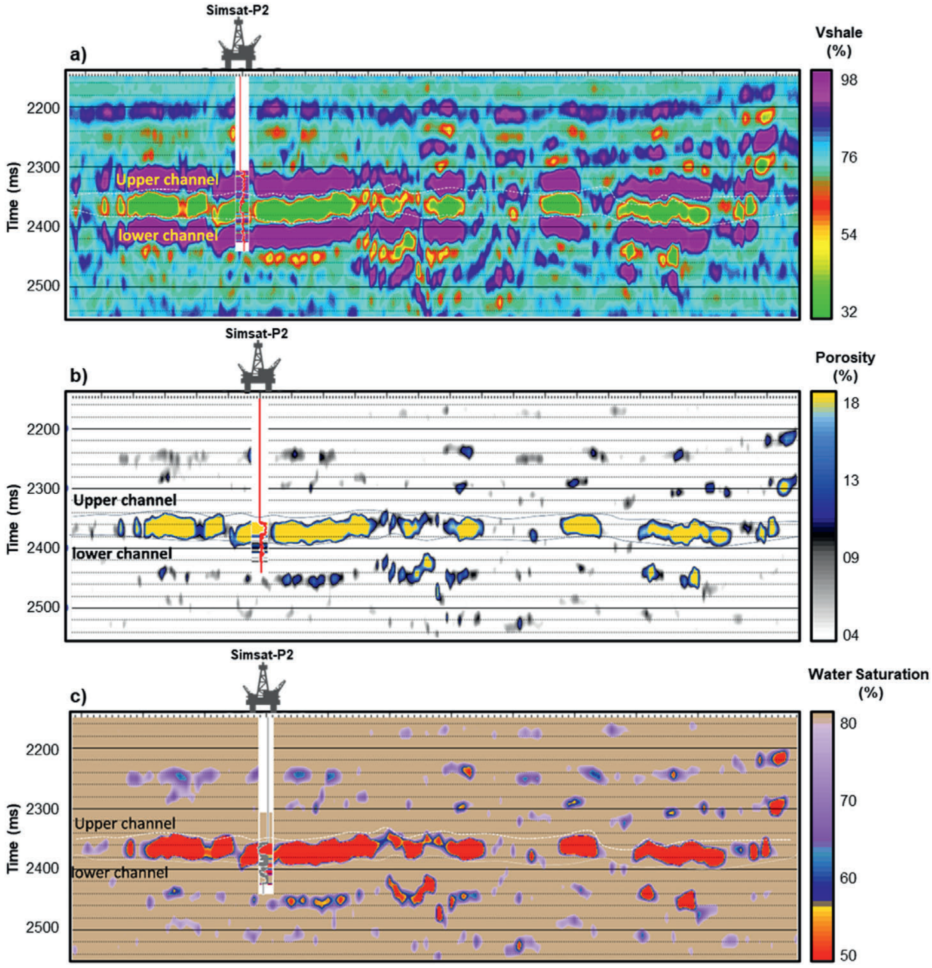


**Fig. 18.** The multilayer feed-forward neural network MLFN results, (a) V shale, (b) porosity and (c) water saturation, across the Simsat P2 well location.

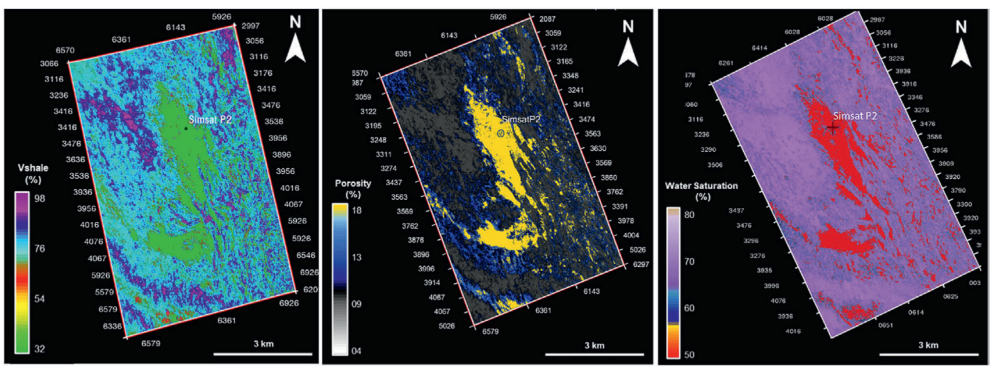


**Fig. 19.** (a) V shale extraction from the application of MLFN over the top Simsat channel. Note that the channel is dominant by green color interpreted as low percentage of shale content where the surrounding area is represented by high value. (b) porosity extraction from the application of MLFN over the top Simsat channel. Note that the channel is dominant by yellow color interpreted as high values above 18% where the surrounding area is represented by high value. (c) Water saturation extraction from the application of MLFN over the top Simsat channel. Note that the channel is dominant by yellow color interpreted as high values above 18% where the surrounding area is represented by high value.

shale volume—along with low average absolute errors, suggesting a robust fit between predicted and actual log data (Figs. 16 and 17). However, we acknowledge that relying on a single well for training limits broader validation. Only the Simsat P2 well was available for this study, which restricted the implementation of cross-validation or testing across multiple locations. Future work should incorporate multi-well datasets and employ cross-validation or probabilistic modeling techniques to quantify prediction uncertainty and ensure generalization across varying reservoir conditions more rigorously.

**Table 1**
Sensitivity chart illustrating the relative contribution of each attribute used in neural network training.

| ATTRIBUTES | WEIGHTS | | |
|---|---|---|---|
| | V Shale [%] | Porosity [%] | Water saturation [%] |
| Energy | 98 | 97 | 99.2 |
| Seismic time | 46 | 70 | 85 |
| Filter 10/50/20 | 70 | 89 | 78 |
| Amplitude weighted phase | 97 | 98 | 99 |
| Dominated frequency | 60 | 76 | 83 |
| Instantaneous phase | 55 | 60 | 63 |
| Inverted Zp | 98 | 99 | 95 |

## 6. Conclusion

This study successfully integrated seismic inversion, spectral decomposition, seismic attributes, and machine learning-based neural network modeling to enhance the quantitative reservoir characterization of the Simsat Field, Offshore Nile Delta. The post-stack seismic inversion effectively distinguished reservoir lithology and fluid distribution, confirming that low-impedance zones correspond to high-porosity, gas-bearing sandstones, while high-impedance values indicate shale-rich formations, which were validated by well log analysis. The well log interpretation of the Simsat P2 well confirmed low shale content (≤15%), high porosity (~13–18%), and hydrocarbon saturation (~52%), aligning with the seismic inversion and attribute analysis results. Spectral decomposition and seismic attributes further improved the identification of reservoir geometry, stratigraphic variations, and potential stratigraphic traps, reinforcing the continuity of high-quality sandstone reservoirs. The multi-layer feed-forward neural network (MLFN) model extended reservoir property predictions beyond well control, achieving high correlation coefficients for porosity, shale volume, and water saturation, which were also validated against well log data. The generated 3D petrophysical property volumes provided a more accurate assessment of reservoir quality, connectivity, and hydrocarbon distribution, reducing exploration uncertainties and improving reservoir modeling and hydrocarbon prospect evaluation. This integrated approach demonstrates that combining seismic inversion with machine learning techniques enhances reservoir characterization and supports better decision-making for well placement, field development, and hydrocarbon production strategies in the West Delta Deep Marine (WDDM) concession and other deep-water settings. Future research should focus on applying this workflow to multi-well datasets with varying geological settings, incorporating cross-validation and uncertainty quantification techniques, and testing alternative machine learning algorithms to further improve prediction robustness and generalization.

## CRediT authorship contribution statement

**Adel Mahmoud Negm:** Writing – original draft, Supervision, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Mohamed I. Abdel-Fattah:** Writing – review & editing, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Mansour H. Al-Hashim:** Writing – original draft, Visualization, Resources, Funding acquisition. **Mohamed Reda:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization.

## Data availability

The datasets generated during and/or analyzed during the current study are not publicly available due to authority restrictions.

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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