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Gas Saturated Sandstone Reservoirs Characterization through Probabilistic Seismic Inversion Using Bayesian Neural Networks

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ABSTRACT - Shallow gas-saturated sandstone reservoirs are prevalent throughout Indonesia, presenting highly lucrative economic prospects that are often hindered by complex geological heterogeneities. Characterization of these reservoirs typically relies on deterministic seismic inversion methods. However, the inherent non-uniqueness of such approaches yields singular solutions devoid of uncertainty quantification. This study proposes a robust probabilistic seismic inversion methodology utilizing a Convolutional Bayesian Neural Network (BNN). By incorporating Monte Carlo (MC) dropout, which forces the stochastic deactivation of hidden nodes during training, the algorithm successfully generates a comprehensive ensemble of predictive realizations. The proposed framework is evaluated using 2D pre-stack synthetic angle gathers (0 to 45°) across two scenarios: a baseline layer-cake model and a structurally complex faulted model incorporating random noise to simulate field-acquired data. Using seismic amplitudes and low-frequency models to simultaneously predict porosity, clay volume, and water saturation, the BNN demonstrates exceptional predictive accuracy on the baseline model, yielding an average Root Mean Square Error (RMSE) of 0.03 and a coefficient of determination (R^2) of 0.9. When applied to the complex faulted model, the predictive fidelity naturally degraded (average R^2 of 0.7 to 0.8; RMSE of 0.09 to 0.15), consistent with the inherent challenges of noise-contaminated data. Furthermore, a comparative analysis against a conventional model-based deterministic inversion reveals that while the deterministic approach better delineates fault architectures via horizon constraints, the BNN framework yields superior quantitative fidelity. Notably, the BNN successfully overcomes the systematic underestimation of porosity inherent in the deterministic acoustic impedance-to-porosity conversion process. The stochastic inversion explicitly produces 2D petrophysical cross-sections detailing the P10, P90, and mean distributions extracted from 50 realizations. Given their high fidelity, the mean distributions are directly applicable for reservoir characterization. Crucially, the probabilistic P10 and P90 boundary percentiles facilitate a comprehensive assessment of in-place hydrocarbon volumes. This study are currently limited to synthetic validation, and subsequent validation with real-field data is necessary before the approach can be practically applied.

Keywords: probabilistic inversion, Bayesian Neural Network, petrophysical properties, gas sandstone.

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1. Introduction

Gas saturated sandstone reservoirs are commonly found across various regions in Indonesia and present highly promising, economically viable targets due to their typically shallow depths (Jin et al., 2024; Shan et al., 2026; Widarsono et al., 2025). Prominent examples include the fluvio-deltaic sequences of the Tunu field in East Kalimantan (Andrieu et al., 2018; Laidlaw et al., 2012) and the Bentu gas field in Central Sumatra (Yuwono et al., 2012). For these fields, accurate reservoir characterization specifically the quantification of fundamental petrophysical properties like porosity, shale volume, and water saturation is critical for assessing economic feasibility and calculating initial hydrocarbons in place (Coimbra & Sampaio 2025; Mahmud et al., 2020; Yusof et al., 2018).

Determining the spatial dimensions and petrophysical parameters of these reservoirs relies heavily on seismic reflection methods, where gas accumulations often present as "bright spot" anomalies due to low gas density (Horozal et al., 2021; Lowrie & Fichtner 2020). Consequently, seismic inversion is widely used for characterization (Putra et al., 2026). However, conventional deterministic seismic inversion methods depend heavily on seismic data quality and typically yield non-unique solutions (Li et al., 2024). This limitation has driven a shift towards probabilistic inversion methods capable of providing multiple possible outcomes to better assess uncertainty (Li et al., 2024).

Increasingly, machine learning algorithms are employed to drive these probabilistic workflows (Grana et al., 2022). For instance, Bayesian Neural Networks (BNN) have been successfully applied for the probabilistic inversion of surface wave data (Zhang & Curtis 2021) and, more recently, for deriving petrophysical properties from seismic reflection data (Grana et al., 2022). Furthermore, (Romero et al., 2025) demonstrated the advantages of BNN-driven probabilistic inversion over conventional deterministic approaches. Despite these advancements, existing studies fall short of addressing the specific non-linear complexities associated with gas-saturated sandstone reservoirs, leaving a critical gap in evaluating BNN performance for this specific geological context.

To address this gap, this study aims to rigorously evaluate the performance of BNN-driven probabilistic inversion specifically tailored for characterizing gas-saturated sandstone reservoirs. Physically, the seismic responses of these reservoirs are highly non-linear and non-unique, making them difficult to predict using standard deterministic neural networks. Such standard networks struggle with this ill-posed inverse problem, as they output single-point estimates without accounting for data or model confidence, often leading to overconfident predictions. In contrast, by replacing deterministic network weights with probability distributions, the proposed BNN approach inherently provides robust uncertainty estimation critical for reliable gas reservoir analysis.

To validate this methodology, a synthetic forward model of a gas-bearing sandstone reservoir is constructed. Utilizing synthetic data is a strategically necessary preliminary step to evaluate the operational behavior and computational requirements of the BNN before field application. Because training and simulating stochastic realizations within a BNN demand significant computational resources, the synthetic model serves as a practical, cost-effective platform to test algorithmic feasibility, optimize network parameters, and ensure stability without the prohibitive overhead of large-scale field datasets. By benchmarking these inversion outputs against the true synthetic model, this study intends to establish a robust reference workflow for future BNN implementations in real-field case studies across Indonesian sedimentary basins.

2. Methodology

2.1 Synthetic seismic data

The present study employs synthetic seismic data derived from a forward modeling approach. The synthetic seismic workflow (Figure 1) is driven by a deterministic rock physics model (Jin et al., 2024). Initially, petrophysical parameters are defined to calculate the P-wave velocity (V_p) utilizing (Han et al., 1986) empirical model (Equation 1). The bulk density (ρ) is subsequently estimated through a linear mixing model (Voigt bound) (Yu 2024), which accounts for the respective volume fractions of the mineral matrix and pore-filling fluids

(Equations 2, 3, and 4).

$$V_p(\text{km/s}) = 5.59 - 6.93\phi - 2.18V_{cl} \quad (1)$$

where V_p and ϕ are the compressional velocity (km/s), the total porosity fraction, and V_{cl} is the clay volume fraction, respectively.

$$\rho_{ma} = (1 - V_{cl})\rho_{quartz} + V_{cl}\rho_{clay} \quad (2)$$

where ρ_{ma} , ρ_{quartz} , and ρ_{clay} are denotes the rock matrix density, represent the densities of the quartz and clay minerals, respectively.

$$\rho_{fl} = S_w\rho_{water} + (1 - S_w)\rho_{hc} \quad (3)$$

where ρ_{fl} , S_w and ρ_{water} are the fluid density in the rock, the water saturation, the water density, and ρ_{hc} is the hydrocarbon density, , respectively.

$$\rho_{bulk} = \phi\rho_{fl} + (1 - \phi)\rho_{ma} \quad (4)$$

where ρ_{bulk} denotes the bulk density, which is fundamentally a function of the respective densities of the pore fluid and the solid rock matrix.

The targeted petrophysical properties comprise clay volume, porosity, and water saturation. Furthermore, the shear-wave velocity (V_s) is estimated based on the proportional relationship between V_p and V_s , applying a specific V_p/V_s ratio for each respective layer (Liu et al., 2023). All petrophysical parameters and input values utilized in the synthetic forward modeling are detailed in Table 1.

Following the derivation of V_p and V_s , the acoustic impedance (AI) is calculated via the following expression (Lowrie & Fichtner 2020):

$$AI = V_p \times \rho_{bulk} \quad (5)$$

where AI is the acoustic impedance, the contrast of which defines the interface between distinct lithologies (Taqiy et al., 2026).

Following the derivation of the AI profile, the reflection coefficient (RC) series can be computed (Fariz et al., 2022). The RC quantifies the reflection magnitude at the geological boundary, yielding either positive or negative values dictated by the impedance contrast across the bounding rock layers (Sukma et al., 2025).

The RC is mathematically determined by the following expression (Lowrie & Fichtner 2020):

$$RC = \frac{AI_2 - AI_1}{AI_2 + AI_1} \quad (6)$$

where RC is the reflection coefficient at the geological boundary, and AI_1 and AI_2 represent the acoustic impedances of the upper and lower layers, respectively.

Following the derivation of the reflectivity series (RC), a convolution process is applied using a 30 Hz zero-phase Ricker wavelet to generate the seismic response. The resulting synthetic data are structured as pre-stack angle gathers (Figure 2). To achieve this, the amplitude variation with angle is modeled utilizing Shuey's 2-term approximation of the exact Zoeppritz interface equations (Kuai et al., 2025).

Table 1.
Petrophysical properties and V_p/V_s ratios applied as inputs for the synthetic forward modeling workflow

Layer	Litologi/fluida	Depth (m)	VClay	Porositas	SW (%)	Vp/Vs ratio
Lapisan 1	Shale	1000 - 1050	0.80	0.05	1.00	2.50
Lapisan 2	Brine Sand	1050 - 1100	0.10	0.25	1.00	2.00
Lapisan 3	Shale	1100 - 1150	0.85	0.05	1.00	2.50
Lapisan 4	Gas Sand	1150 - 1200	0.05	0.30	0.20	1.60
Lapisan 5	Shale	1200 - 1250	0.80	0.05	1.00	2.50

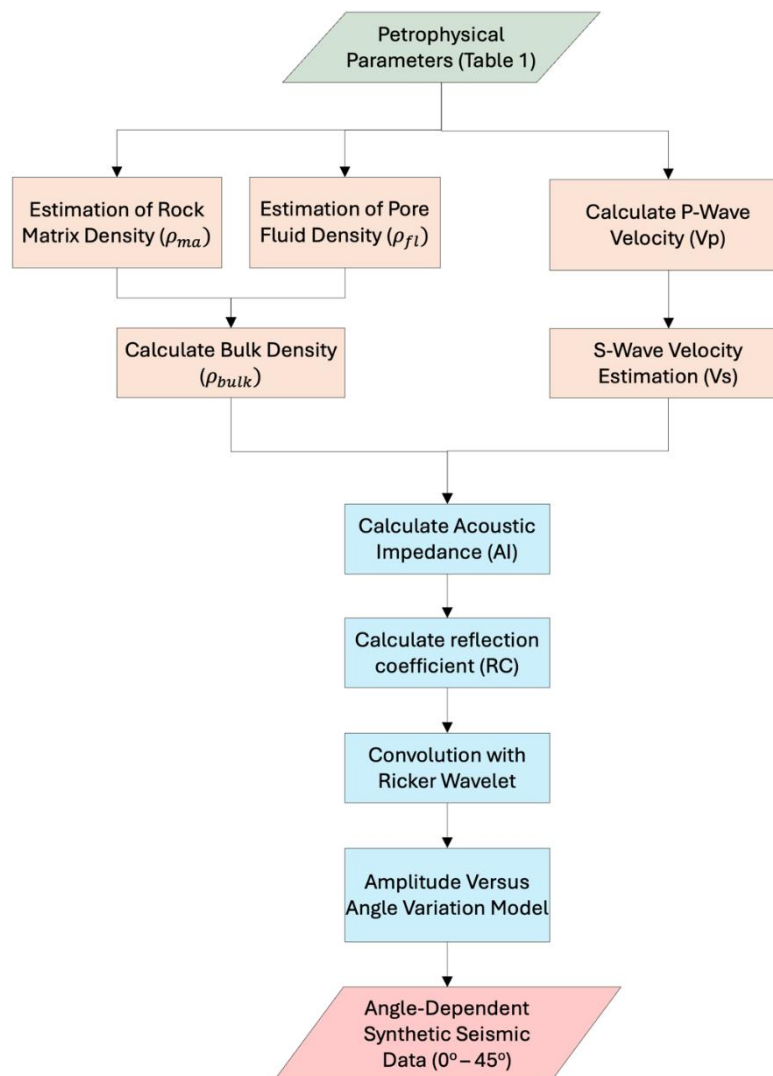


Figure 1.
Workflow for generating angle-dependent synthetic seismic data

$$R(\theta) = R_0 + G \sin^2 \theta \quad (7)$$

where $R(\theta)$, R_0 , and G are defines the angle-dependent reflection coefficient, denote the Amplitude Variation with Angle intercept and gradient, respectively. The synthetic forward model was parameterized to carefully reflect typical geological conditions of shallow gas-bearing siliciclastic sequences. A 30 Hz zero-phase Ricker

wavelet was selected, as it represents the dominant seismic frequency conventionally observed for shallow to intermediate reservoir targets. Layer thicknesses were deliberately set to 50 m to comfortably exceed the seismic tuning thickness, thereby isolating the BNN's evaluation to pure petrophysical variations without the confounding interference of thin-bed effects. Furthermore, the applied V_p/V_s ratios (e.g., approximately 1.6 for gas sands and >2.0 for background shales) were assigned based on established empirical rock physics trends for clastic rocks.

To generate the pre-stack response, synthetic angle gathers were modeled over an incident angle range of 0° to 45° with a step size of 5° . The 45° far-angle limit is strictly necessary to capture the diagnostic far-offset AVO anomalies typically associated with gas-saturated sandstones, while the 5° increment provides sufficient angular resolution for generating partial stacks without incurring excessive computational redundancy. Finally, the synthetic trace was replicated 100 times to construct a pseudo-2D seismic section comprising 100 Common Depth Points (CDPs). This lateral replication creates a controlled spatial window, predictions prior to real-field application.

To ensure the synthetic data closely resembles field measurements, noise and geological features were incorporated into the model. The applied noise is Gaussian noise, which is a type of normally distributed random noise, using a noise level parameter of 0.005 to represent its standard deviation. Furthermore, to better reflect realistic subsurface conditions, a normal fault was introduced into the model. In this configuration, the footwall acts as a structural trap saturated with gas hydrocarbons, whereas the hanging wall represents a brine-saturated zone devoid of hydrocarbons.

2.2 Bayesian neural network inversion

Within the realm of statistical and computational inverse problems, the Bayesian framework remains the most widely adopted probabilistic approach (Fernandes et al., 2024). The primary objective of this methodology is to estimate the posterior probability distribution of the model parameters, denoted as $P(m|d)$ (Grana et al., 2022). This posterior distribution is mathematically derived via Bayes' theorem (Li, Liu, et al., 2024), expressed as follows :

$$P(m|d) = P(d|m)P(m)/P(d) \quad (8)$$

where $P(m)$ and $P(d|m)$ are the posterior is evaluated as the product of the prior model probability distribution, the data likelihood function, respectively. (Li et al., 2024). This product is subsequently normalized by the marginal likelihood of the data (the evidence), $P(d)$, ensuring the probability density integrates to unity: $\int P(m|d)dm = 1$ (Grana et al., 2022).

Evaluating the exact Bayesian formulation (Equation 8) is notoriously intractable, as computing the normalizing constant (the marginal likelihood) analytically is virtually impossible for non-linear physical forward operators (Gou et al., 2022). To circumvent this analytical bottleneck, Monte Carlo methods are employed. Instead of a deterministic calculation, this approach stochastically generates thousands of model realizations from the prior distribution $P(m)$ and evaluates their data fit via the likelihood function $P(d|m)$, iteratively constructing a robust empirical approximation of the desired posterior distribution (Li et al., 2024). The most robust Monte Carlo strategy for circumventing the intractable Bayesian evidence is the Markov chain Monte Carlo (MCMC) framework, notably the Metropolis-Hastings algorithm (Li et al., 2024). This method evaluates a proposed model realization (m') relative to the current state (m_i) by calculating their posterior probability ratio (Zhang & Curtis 2021). Because the marginal likelihood $P(d)$ is invariant for an observed dataset, it elegantly cancels out in the evaluation, significantly alleviating the computational burden (Fernandes et al., 2024). Mathematically, the acceptance probability of the proposed state is defined as follows:

$$P_a = \min \left(\frac{P(d|m')P(m')}{P(d|m_i)P(m_i)} \times \frac{g(m_i|m')}{g(m'|m_i)}, 1 \right) \quad (9)$$

where P_a , m' , and g are the final value that determines the probability of the new guess being accepted, m_i represents the current model (current state), the newly proposed model (proposed state), and the proposal distribution, respectively.

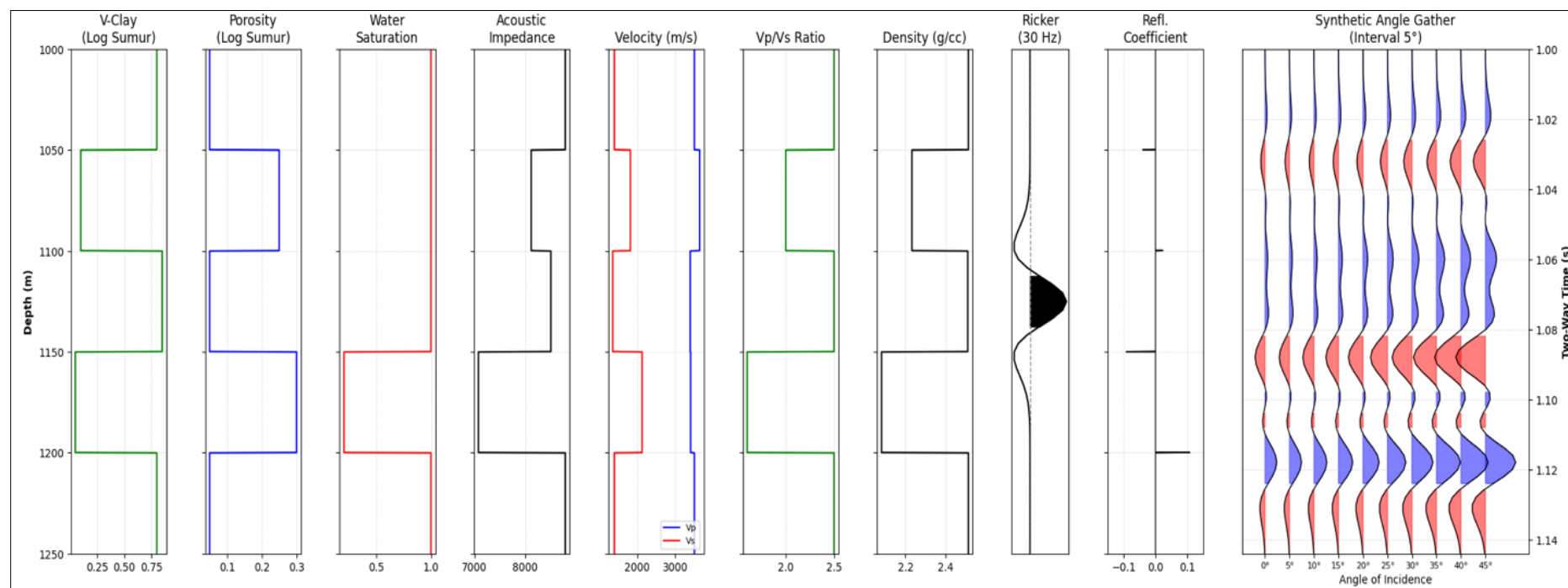


Figure 2.
Synthetic seismic forward modeling as a function of angle

Deep learning approaches have established themselves as formidable computational tools for seismic inversion (Simutè et al., 2023), where the fundamental objective is to map seismic responses back to reservoir petrophysical properties, such as porosity, clay volume, and water saturation (Li et al., 2024). In this architecture, artificial neural networks are utilized to derive the inverse mapping approximation, $g \cong \tilde{f}^{-1}$, where f represents the deterministic rock physics forward modeling operator (Zhang & Curtis 2021). Diverging from conventional stochastic optimization schemes, these deep layered networks efficiently characterize the intricate, non-linear mappings between observed seismic data and subsurface model parameters (Siahgoli et al., 2025).

Given that seismic data are fundamentally recorded as time-series signals, the use of Recurrent Neural Network (RNN) architectures (Siahgoli et al., 2025), particularly the Long Short-Term Memory (LSTM) variant, is highly crucial due to their ability to capture temporal dependencies (Sun et al., 2024). The subsurface model properties, m , are extracted from the network's hidden states, z . Mathematically, the transformation within this network with L hidden layers (Li et al., 2024) is formulated as:

$$m = h(w_L z_L + b_L) \quad (10)$$

where the hidden states are sequentially updated across successive time steps using the following Equation 11

$$z_l = g(w_{l-1} z_{l-1} + b_{l-1}) \quad (11)$$

for $l = 1, \dots, L$, where $\{w\}_{1,\dots,L}$ and $\{b\}_{1,\dots,L}$ represent the trainable weight matrices and bias vectors at the l -th layer, respectively, and g and h denote the non-linear activation functions governing the information flow.

Despite their capacity to yield robust sequential predictions, purely deterministic RNN architectures are often inadequate due to their inability to quantify the intrinsic uncertainties ubiquitous in geophysical inverse problems (Xiang et al., 2026). To address this limitation, the neural network is embedded within a probabilistic Bayesian framework (Chala & Ray 2025). Under the assumption of independent Gaussian measurement noise, the likelihood function mapping the observed data d to the complete set of network parameters θ (Li et al., 2024) is defined as follows:

$$P(d|\theta) = \prod_{i=1}^n \mathcal{N}(f(m(\theta))_i; d_i; \sigma_i^2) \quad (12)$$

where $P(d|\theta)$, $\mathcal{N}(\dots)$, $f(m(\theta))_i$, d_i , and σ_i^2 are defines the data likelihood function, denotes the Gaussian probability density function, represent the i -th modeled response and observed data, and the variance characterizing the uncertainty or noise of the i -th measurement, respectively.

The final stage of this probabilistic petrophysical inversion workflow entails estimating the comprehensive probability distribution of the network parameters by applying Bayes' theorem (Li et al., 2024). Conditioned on the observed data d , the posterior distribution of the network parameters θ is evaluated via the following expression:

$$P(\theta|d) = P(d|\theta)P(\theta)/P(d) \quad (13)$$

where $P(\theta|d)$, $P(\theta)$, and $P(d)$ are defines the posterior probability distribution, represents the prior probability, and denotes the marginal likelihood, often referred to as the Bayesian evidence, respectively.

2.1 Model hyperparameter estimation

The proposed computational framework bypasses the conventional seismic inversion by introducing a direct petrophysical inversion approach (Grana et al., 2022). Instead of first extracting elastic properties (V_p , V_s , and ρ) from seismic amplitudes and subsequently deriving petrophysical parameters through empirical relations, the artificial neural network comprising Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) directly interprets pre-stack seismic data (near, mid, and far partial stacks) (Zhang & Curtis 2021). Through this direct mapping, the neural network functions as an inverse model that outputs simultaneous predictions for porosity (ϕ), clay volume (V_{clay}), and water saturation (S_w) in a single computational step, avoiding the propagation of errors inherent in intermediate deterministic calculations (Grana et al., 2022).

Within this Bayesian Neural Network (BNN) framework, the fundamental physical laws are exclusively utilized as an evaluation mechanism rather than for direct prediction (Romero et al., 2025). The output variables from the neural network are fed into a forward physical model to validate their geological plausibility (Gou et al., 2022). Specifically, the predicted petrophysical parameters (ϕ , V_{clay} , and S_w) serve as inputs for the Dvorkin-Gassmann soft sand model (Li et al., 2024), which translates these compositional and fluid properties into elastic wave velocities (V_p , V_s) and bulk density (ρ). Subsequently, the Aki-Richards approximation calculates the angle-dependent reflection coefficients to generate synthetic partial-stack seismic traces (Li et al., 2024). The algorithm then compares these synthetic traces with the observed field data, utilizing the misfit to backpropagate and adjust the neural network weights if the physical constraints are violated (Zhang & Curtis 2021).

To establish a robust baseline and isolate the network's internal predictive capability, a purely data-driven mode can be implemented by bypassing the forward seismic modeling operators (Simutè et al., 2023). In this configuration, the objective function minimized by the optimization algorithm depends solely on the petrophysical prediction error, devoid of physical regularizers (Grana et al., 2022). The total loss function is mathematically defined as:

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{property} \quad (14)$$

where $\mathcal{L}_{total}$, and $\mathcal{L}_{property}$ are denotes the overall loss value optimized by the network during training, and represents the data-driven property loss function. The symbol α is a user defined hyperparameter weight that controls the strictness of the model in fitting the well log data constraints, respectively.

This data-driven evaluation relies on the Mean Squared Error (MSE) to quantify the discrepancy between the neural network predictions and the actual well log targets (Zhang & Curtis 2021). The property loss function accounts for the three predicted parameters across all temporal samples and seismic traces within a given training batch (Romero et al., 2025). The formulation is expressed as:

$$\mathcal{L}_{property} = \text{MSE}(\hat{\mathbf{m}}, \mathbf{m}) = \frac{1}{N \times N_t} \sum_{i=1}^N \sum_{t=1}^{N_t} \sum_{j=1}^3 (\hat{m}_{i,t,j} - m_{i,t,j})^2 \quad (15)$$

where $\hat{\mathbf{m}}$, $\mathbf{m}$, denote the overall predicted, true petrophysical property matrices, respectively. Specifically, $\hat{m}_{i,t,j}$ represents the predicted value of property index j (where $j = 1$ corresponds to ϕ , $j = 2$ to V_{clay} , and $j = 3$ to S_w) at time or depth sample t within the seismic trace i . The parameter $m_{i,t,j}$ denotes the corresponding true target value derived from the training well logs. The variables N and N_t represent the total number of spatial seismic traces in a single training batch and the total number of temporal samples per trace, respectively.

Although the employed loss function resembles that of a standard deterministic neural network, the Bayesian nature of the framework is rigorously derived from its stochastic architecture (Chala & Ray 2025). During training, the network optimizes the standard MSE; however, Bayesian inference is achieved through the continuous application of Monte Carlo (MC) Dropout before each evaluation layer (Grana et al., 2022). From a theoretical perspective, minimizing the MSE combined with L2 regularization applied via the weight decay parameter in the Adam optimization algorithm is mathematically equivalent to maximizing the Evidence Lower Bound (ELBO) in Variational Inference (Li et al., 2024). This structural approach allows the network to capture complex predictive distributions without the profound computational burden of explicitly calculating variational divergence integrals (Zhang & Curtis 2021).

During the inference phase, the stochastic nature of the network is leveraged to quantify model uncertainty and extract robust petrophysical mappings (Grana et al., 2022). The predictive mean and its associated epistemic uncertainty are obtained by performing multiple stochastic forward passes (MC Loop) on the same input data, intentionally deactivating random neurons in each iteration (Li et al., 2024). The expected value of the target property prediction is approximated by the empirical mean of these stochastic realizations (Li et al., 2024):

$$\mathbb{E}[\hat{\mathbf{m}}] \approx \frac{1}{N_{MC}} \sum_{k=1}^{N_{MC}} \hat{\mathbf{m}}_k \quad (16)$$

where $\mathbb{E}[\hat{\mathbf{m}}]$ denotes the expected value (predictive mean) of the petrophysical properties. The term N_{MC} represents the total number of Monte Carlo simulation iterations (realizations) performed during the inference phase, and the symbol $\hat{\mathbf{m}}_k$ represents the stochastic property vector output generated at the k -th iteration. This methodology ensures that the final inversion results are grounded in probabilistic estimation, providing critical uncertainty quantification for advanced reservoir characterization.

Figure 3 illustrates the proposed data-driven Bayesian Neural Network (BNN) workflow utilized for the stochastic inversion of petrophysical properties. The architecture takes seismic partial stacks (near, mid, and far incident angles) as inputs. Unlike deterministic networks, the hidden layers of the BNN represent their weights as probability distributions, employing Monte Carlo dropout to generate an ensemble of predictive realizations. Ultimately, the network outputs the estimated petrophysical properties which are iteratively optimized by minimizing a data-driven objective function, defined by the Mean Squared Error (MSE) between the predicted spatial properties and the actual well log measurements.

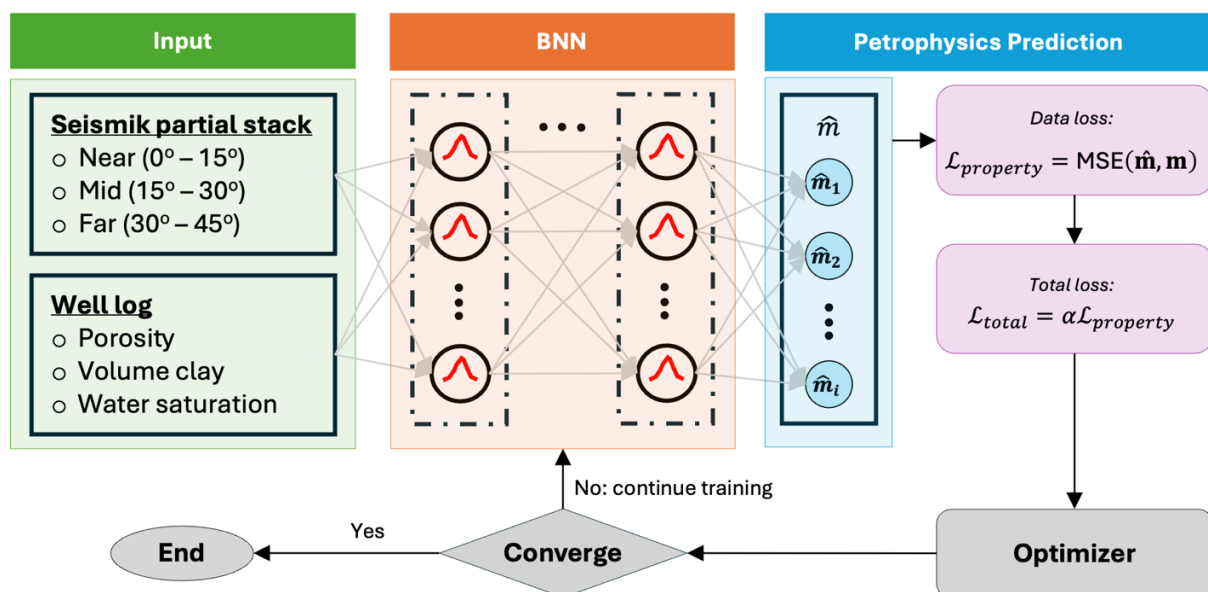


Figure 3.
Workflow of the Bayesian Neural Network (BNN) process

3. Result and discussion

Synthetic Seismic Data Analysis

The generated synthetic seismic gathers (Figure 2), augmented to simulate 100 Common Depth Points (CDPs), are subsequently utilized to generate partial stacks. To realistically represent lateral variation (heterogeneity) typical of actual reservoirs, this initial setup employs a continuous "layer-cake" geological model. This step ensures that while the base geological framework remains horizontally stratified and continuous, the seismic amplitudes and waveforms vary laterally from trace to trace.

Utilizing these 100 heterogeneous CDPs to generate the partial stacks is crucial; it provides a controlled 2D spatial window to test the BNN's lateral stability, and its capability to capture continuous uncertainty bounds across laterally varying seismic responses before analyzing the final prediction results. This partial stacking procedure involves integrating the synthetic angle gathers over specific angular bounds. Stacking is performed across incidence angles of 0° – 15° to derive the near-angle stack, 15° – 30° for the mid-angle stack, and 30° – 45° for the far-angle stack (Figure 4).

The synthesized seismic amplitudes span a range of 1 to -1, exhibiting distinct variations across the strata. At the lithological boundaries, the seismic response manifests as a trough for sandstone intervals and a peak for shale formations. This polarity behaviour is dictated by the use of a zero-phase wavelet featuring a dominant frequency of 30 Hz (Figure 4). Notably, the amplitude signature within the gas-saturated reservoirs displays a substantially stronger negative magnitude relative to the water-bearing reservoirs (Figure 4).

In addition to the partial stack seismic data, the BNN inversion framework also requires input from petrophysical properties. For the purpose of this study, the predefined petrophysical properties (Table 1) are augmented to match the spatial dimensions of the partial stack data, yielding an ensemble of 100 seismic traces (Figure 4). In field-scale applications, this population procedure is typically achieved via geostatistical simulation. Integrating data from a dense well network, characteristic of development fields, significantly enhances the accuracy of the resulting spatial model.

To comprehensively evaluate the robustness of the BNN inversion framework, this baseline layer-cake model will be systematically compared against a more complex structural model. This subsequent structural model incorporates a normal fault to simulate realistic geological traps, wherein the footwall acts as a gas-saturated reservoir and the hanging wall represents a brine-bearing zone devoid of hydrocarbons. Comparing these two scenarios allows for a critical assessment of the BNN's performance in resolving both laterally continuous formations and abrupt structural discontinuities.

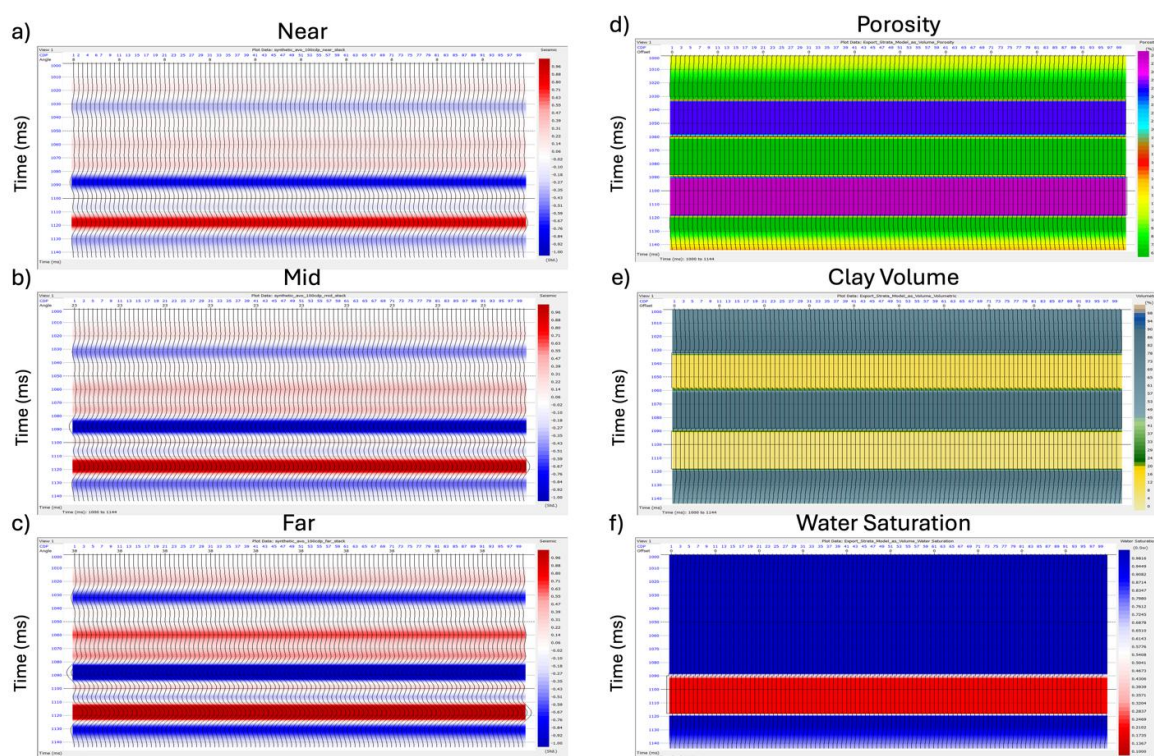


Figure 4.

Seismic partial angle stacks for the layer-cake model:

(a) Near-angle stack, (b) Mid-angle stack, and (c) Far-angle stack; alongside the corresponding petrophysical sections: (d) Porosity, (e) Clay volume, and (f) Water saturation

To quantify the predictive uncertainty, the Monte Carlo (MC) sampling technique was employed with 50 realizations. This specific number of iterations was selected to optimize computational efficiency while still generating a robust probability distribution for the targeted rock properties. By injecting stochasticity into the network during each realization, the model produces a range of outputs, allowing for the estimation of the posterior distribution and the extraction of the mean prediction, albeit with a slightly lower probability curve resolution compared to higher iteration counts. The training phase was configured with a maximum of 150 epochs, limiting the number of complete learning passes through the entire dataset. The learning objective in this BNN approach

was governed exclusively by the property loss, which was scaled by a weighting parameter α set to 1. This parameter serves as a definitive multiplier for the Mean Squared Error (MSE) computed between the predicted network outputs and the actual well log data.

Table 2.
Performance Evaluation of BNN Hyperparameters for Layer Cakes Model

	Porosity	Clay volume	Water saturation
RMSE	0.0203	0.0350	0.0366
R ² Score	0.9598	0.9891	0.9867
Pearson (r)	0.9845	0.9963	0.9959

Furthermore, the optimization process utilized a batch size of 30, indicating that the network's weights were updated iteratively after evaluating subsets of 30 samples. This mini-batch gradient descent approach was implemented to ensure stable optimization steps and manage computational memory usage effectively during the training process.

The foundation of the model's predictive capability relies heavily on the training dataset, which is initially anchored by data extracted from 15 selected wells. In data-driven architectures such as BNNs, maximizing the volume and diversity of training data directly enhances the network's predictive accuracy and generalization. However, relying solely on isolated well logs is insufficient to capture continuous spatial heterogeneity. To adequately represent this geological heterogeneity and to simulate practical field conditions where well data is typically sparse, these 15 wells serve as primary geostatistical control points. The training dataset is subsequently expanded by extracting additional samples along the seismic traces, where the corresponding petrophysical target values are populated based on spatial geostatistical distributions derived from the initial well data. This approach ensures that the BNN is trained on a comprehensive, heterogeneous dataset that bridges the spatial gaps between well locations.

Given the relatively abbreviated training duration of 150 epochs, the network's capacity to fully generalize the subsurface heterogeneity from these 15 training wells is a critical point of evaluation. Subsequent monitoring of the loss convergence curve is imperative to ensure that the model does not exhibit underfitting and has adequately captured the essential data features.

The application of the BNN framework with the specified parameters results in an average Root Mean Square Error (RMSE) of 0.03 (a 3% error rate) across the predictions of the three petrophysical properties. Additionally, the average coefficient of determination (R^2) is 0.9, indicating that 90% of the data variance is successfully explained by the model. These evaluation metrics demonstrate a robust predictive performance for porosity, clay volume, and water saturation. A comprehensive summary of these quantitative results is presented in Table 2.

The loss convergence curve (Figure 5) illustrates that the BNN model has undergone optimal and stable learning without exhibiting any signs of overfitting or underfitting. From the initiation of training until approximately epoch 30, both the training and validation losses undergo a steep, concurrent decline, demonstrating the network's swift capacity to delineate the non-linear patterns within the petrophysical data.

Subsequent to epoch 40 and extending to the final training limit at epoch 150, both curves flatten asymptotically towards zero and remain closely superimposed. This seamless convergence validates that the prescribed hyperparameter configuration is sufficient to establish an equilibrium state, thereby substantiating the model's robust generalization ability when applied to unseen well log data.

Petrophysical property estimations obtained via the Bayesian Neural Network (BNN) framework demonstrate an exceptional degree of fidelity to the ground-truth data (Figure 6). This synthetic dataset is ideal for BNN training because it combines complex, non-linear rock physics relationships with error-free labels. Furthermore, integrating geostatistical variance simulates the inherent ambiguity of real seismic data, providing the perfect environment for the BNN to simultaneously learn deterministic mappings and explicitly quantify underlying uncertainties via probabilistic bounds (e.g., P10 and P90). Analysis of the 1D vertical profiles for porosity, clay

volume, and water saturation reveals that the mean prediction curve accurately delineates both the macroscopic trends and localized anomalies of the reference well across the seismic time interval.

A notable merit of this architecture is its proficiency in resolving sharp lithological boundaries and abrupt property transitions, such as the distinct step-like changes observed at approximately 1.78 s, 1.84 s, and 1.91 s (Figure 6). The network effectively reconstructs these high-frequency features without suffering from excessive smoothing, thereby preserving the vertical integrity of the target strata. Unlike conventional model-based inversions that rely heavily on low-frequency starting models and strict deterministic regularizations that inherently dampen sharp boundaries, the BNN directly maps band-limited seismic responses to broadband well log properties. Furthermore, by drawing stochastic realizations from the posterior weight distributions, the BNN preserves the sharp, non-linear petrophysical contrasts (such as abrupt gas-sand interfaces) across individual predictions, avoiding the over-smoothed outputs typical of single-point deterministic averaging.

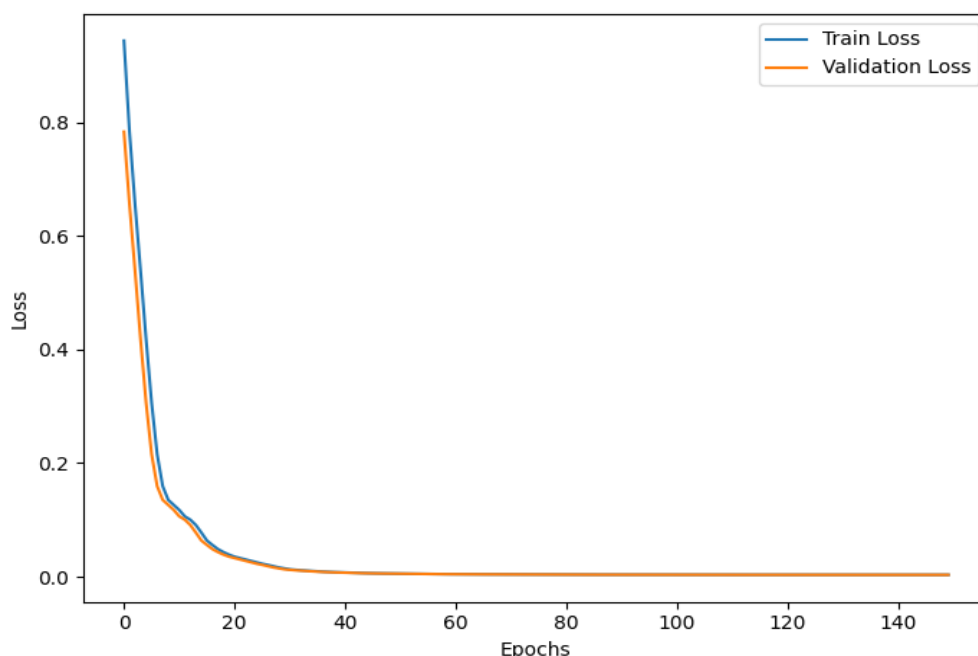


Figure 5.
Training and validation loss convergence curves

Beyond yielding precise mean predictions, the deployment of this stochastic framework proves highly robust in uncertainty quantification. The uncertainty bands, defined by the P10 and P90 percentiles (Figure 6), comprehensively encapsulate the probabilistic output range of the model, effectively providing a range of possible realizations. Crucially, the ground-truth logs consistently fall within this confidence interval across the entire profile, corroborating the validity of the model's statistical inferences.

The well-calibrated, relatively uniform width of the uncertainty bounds signifies a consistent degree of predictive confidence throughout the reservoir interval. This behaviour validates the stability of the BNN architecture (Figure 6), demonstrating its capacity for robust generalization while simultaneously mitigating the risks of overconfidence or overfitting. Such stability is particularly vital when characterizing complex geological environments, ensuring that the model provides reliable estimates for both lithology and fluid content.

Quantitative assessment via residual point plots on the blind well substantiates the outstanding precision of the developed inversion framework (Figure 7). The scatter distribution of the residual points across all three petrophysical properties is densely and symmetrically clustered around the zero-error reference line. Notably, for porosity and water saturation estimates, the vast majority of deviations are confined to a highly constrained margin (ranging from -0.05 to 0.05 v/v).

This uniform dispersion, lacking any severe directional skew, demonstrates that the model is fundamentally devoid of detrimental systematic bias (Figure 7). The network displays no persistent propensity for aggregate overestimation or underestimation; rather, the remaining minor random errors merely characterize the acceptable bounds inherent to the stochastic nature of Bayesian modeling.

Furthermore, the 1D spatial analysis of the residual plots facilitates the precise localization of geological intervals characterized by peak reconstruction complexity. It is apparent that the marginally more pronounced residual spikes (approaching ± 0.1 v/v), particularly within the clay volume profile, are acutely localized and strictly confined to time intervals of approximately 1.78 s, 1.84 s, and 1.91 s. These localized deviation maxima directly correlate with stratigraphic lithology interfaces where the ground-truth data display abrupt, discrete shifts in petrophysical properties (blocky transitions).

The observation that the maximum errors are strictly isolated at these layer boundaries with their magnitudes firmly maintained within a highly acceptable analytical tolerance further corroborates the robust validity of the model in reconstructing subsurface formation heterogeneity without introducing spurious computational artifacts.

Following the initial validation, the BNN inversion framework was deployed across the full spatial extent of the partial stack seismic data. This yielded 2D petrophysical property sections for the P10, P90, and mean values, aggregated from 50 stochastic realizations (Figure 8). The performance of the BNN inversion was then rigorously evaluated by comparing the predicted outputs against the ground-truth well data across the entire seismic volume.

The 2D spatial distribution of the inverted petrophysical properties demonstrates the exceptional capability of the Bayesian Neural Network (BNN) framework in reconstructing subsurface stratigraphy (Figure 8). A direct comparison between the BNN's mean predictions and the actual ground-truth models reveals a high degree of spatial fidelity and lateral consistency across all seismic traces.

The network successfully captures the layer-cake geometries and the thicknesses of the target formations without introducing artificial horizontal smoothing artifacts. Sharp lithological boundaries that separate the sealing shale layers from the target clean sandstones clearly visible in both the clay volume and porosity profiles are precisely mirrored in the network's deterministic output. This confirms the proficiency of the data-driven architecture in handling high-frequency spatial transitions across contrasting geological facies.

Crucially, the effectiveness of the BNN framework is highlighted by its precision in fluid discrimination, which is paramount for characterizing gas-saturated sandstone reservoirs. The 2D water saturation profile generated by the model flawlessly identifies and spatially localizes a distinct, massive low-saturation anomaly. This anomaly is sharply bounded and maintains the integrity of the fluid contacts continuously across the lateral extent of the target zone.

By successfully correlating this low water saturation interval with the corresponding high porosity and low clay volume zones, the model unambiguously delineates the gas-bearing sandstone reservoir. The seamless match between the predicted spatial fluid distribution and the true subsurface model validates the BNN's robustness in complex fluid and lithology identification.

Beyond accurate deterministic mapping, the stochastic nature of the BNN provides critical spatial uncertainty quantification, visualized through the P10 and P90 percentile panels (Figure 8). These uncertainty bounds offer a continuous probabilistic assessment of the inverted properties, effectively capturing the model's predictive confidence. An analysis of these uncertainty profiles reveals that while the absolute property magnitudes exhibit expected statistical variance, the macroscopic structural framework and the spatial integrity of the gas-saturated sandstone remain highly consistent.

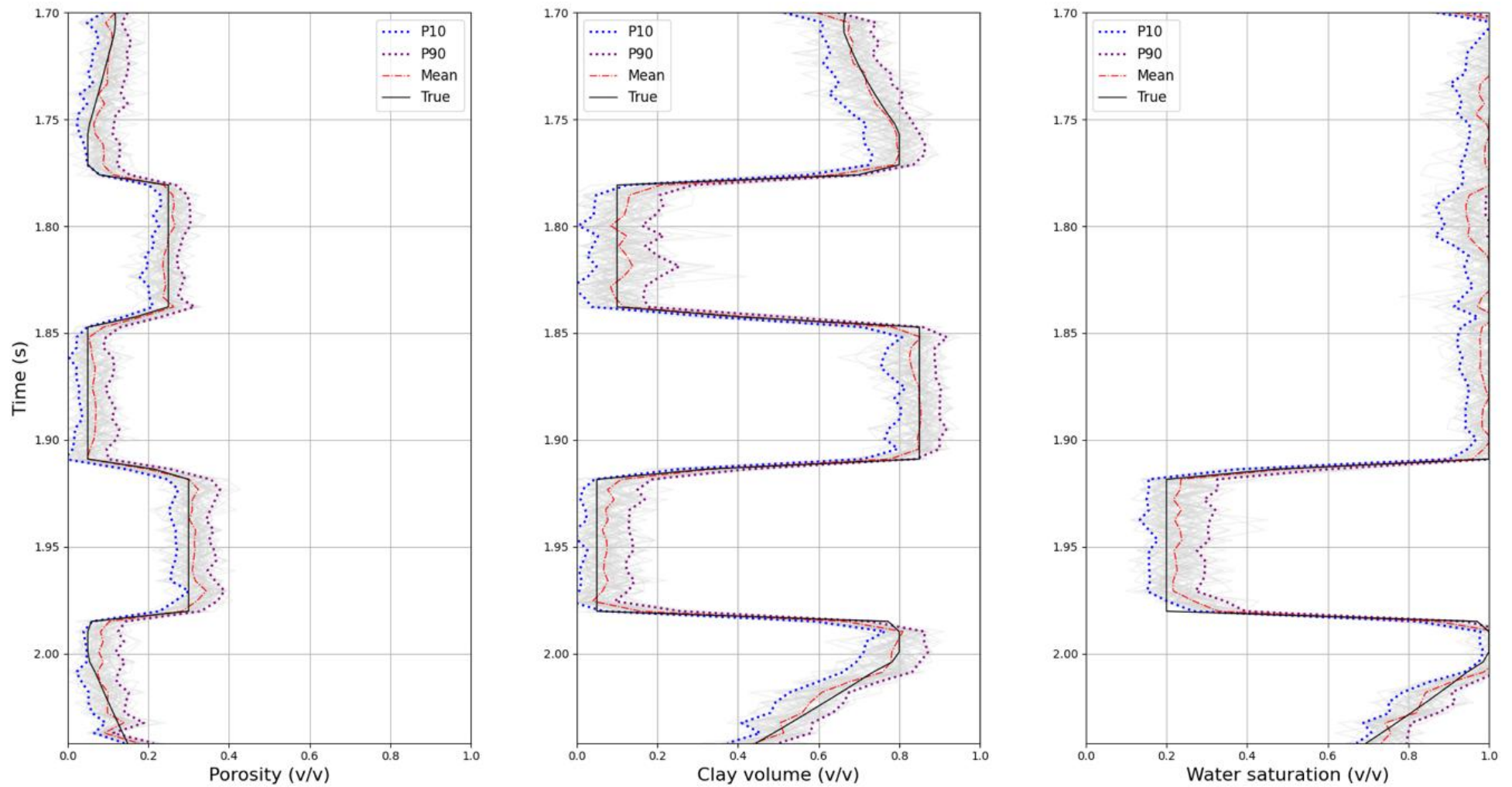


Figure 6.
1D BNN-derived petrophysical properties for layer cakes model: porosity (left), clay volume (center), and water saturation (right)

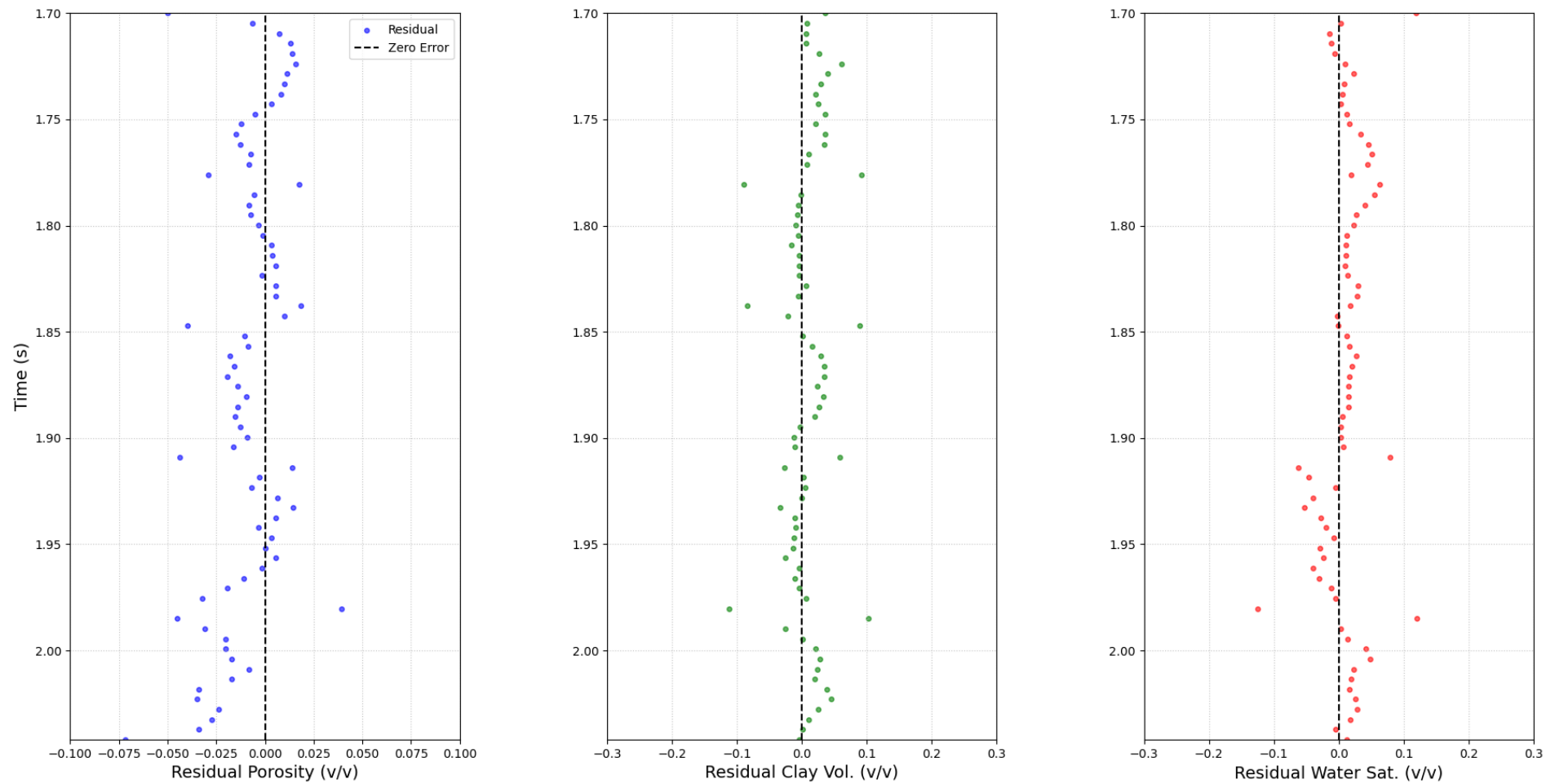


Figure 7.
Prediction residuals for (left) porosity, (center) clay volume, and (right) water saturation, derived from actual petrophysical data.

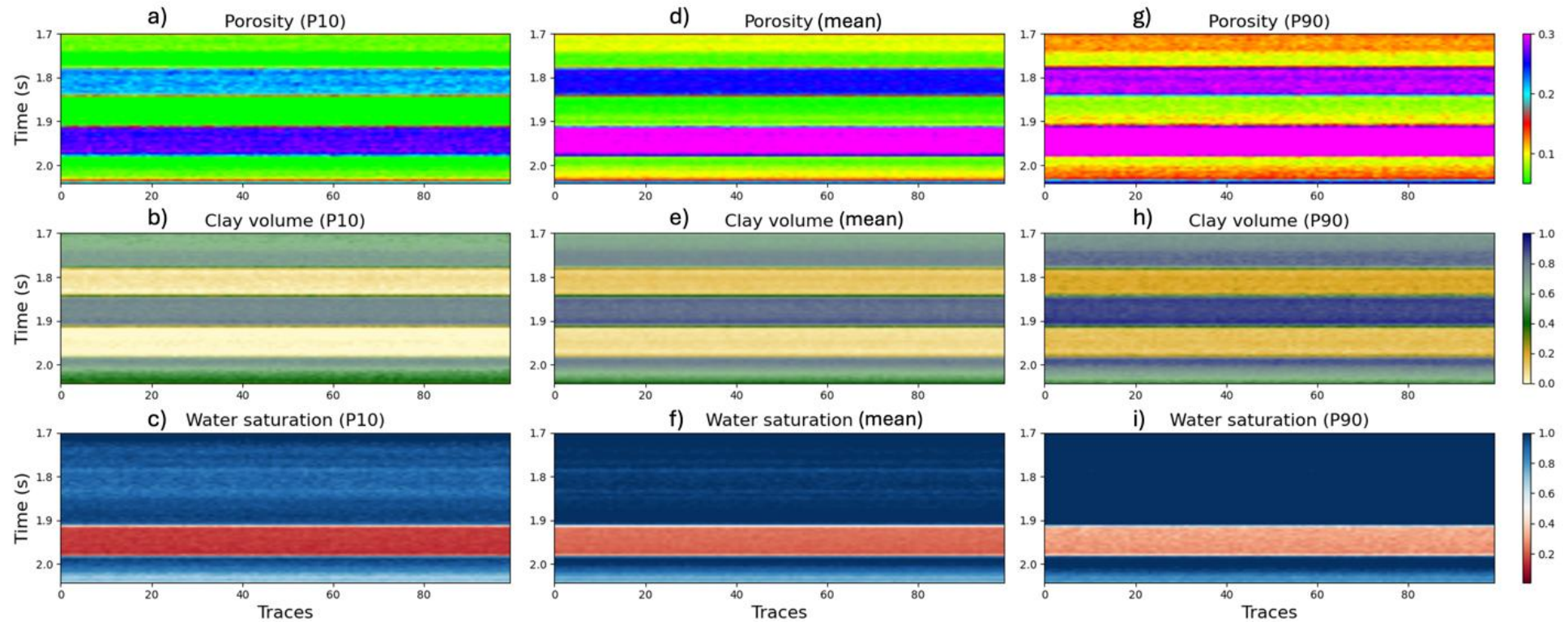


Figure 8.

2D petrophysical sections of a layer-cake model generated via BNN inversion, illustrating the P10 stochastic realizations for (a) porosity, (b) clay volume, and (c) water saturation; the mean distributions for (d) porosity, (e) clay volume, and (f) water saturation; and the P90 realizations for (g) porosity, (h) clay volume, and (i) water saturation.

The critical low-saturation anomaly is robustly preserved even at the outer confidence limits (P10 and P90), significantly reducing interpretive ambiguity. This uniform and narrow confidence interval across the traces proves that the network generalizes well spatially without suffering from instability or overfitting. Consequently, this distinguishing characteristic sets the BNN framework apart, as it uniquely yields comprehensive uncertainty quantification alongside the derived petrophysical properties.

These preliminary findings necessitate further investigation, particularly through the integration of field-acquired seismic data, which is inherently subjected to recording noise. The current synthetic modelling framework does not fully account for such noise characteristics, and therefore may not perfectly mirror real-world subsurface conditions. Nonetheless, this study provides robust validation that the probabilistic BNN inversion framework is a highly viable approach for characterizing gas-saturated hydrocarbon reservoirs.

In addition to using the layer-cake model, a comparison will be made with another model. This second model adds random noise and a fault that separates the gas-filled sandstone layer in the footwall from the brine zone in the hanging wall (Figure 9). This model was created to represent subsurface conditions that resemble actual measured seismic data.

This complex model is constructed utilizing control data from two synthetic wells: Well-20 located in the footwall block and Well-70 situated in the hanging wall block. The petrophysical properties of Well-20 replicate those of the baseline model shown in Figure 2, featuring a gas-saturated sandstone reservoir in layer 4 with correspondingly low water saturation. Conversely, Well-70 simulates a non-hydrocarbon-bearing scenario, wherein the sandstone interval is entirely devoid of gas and reaches a water saturation of 100% (Figure 9).

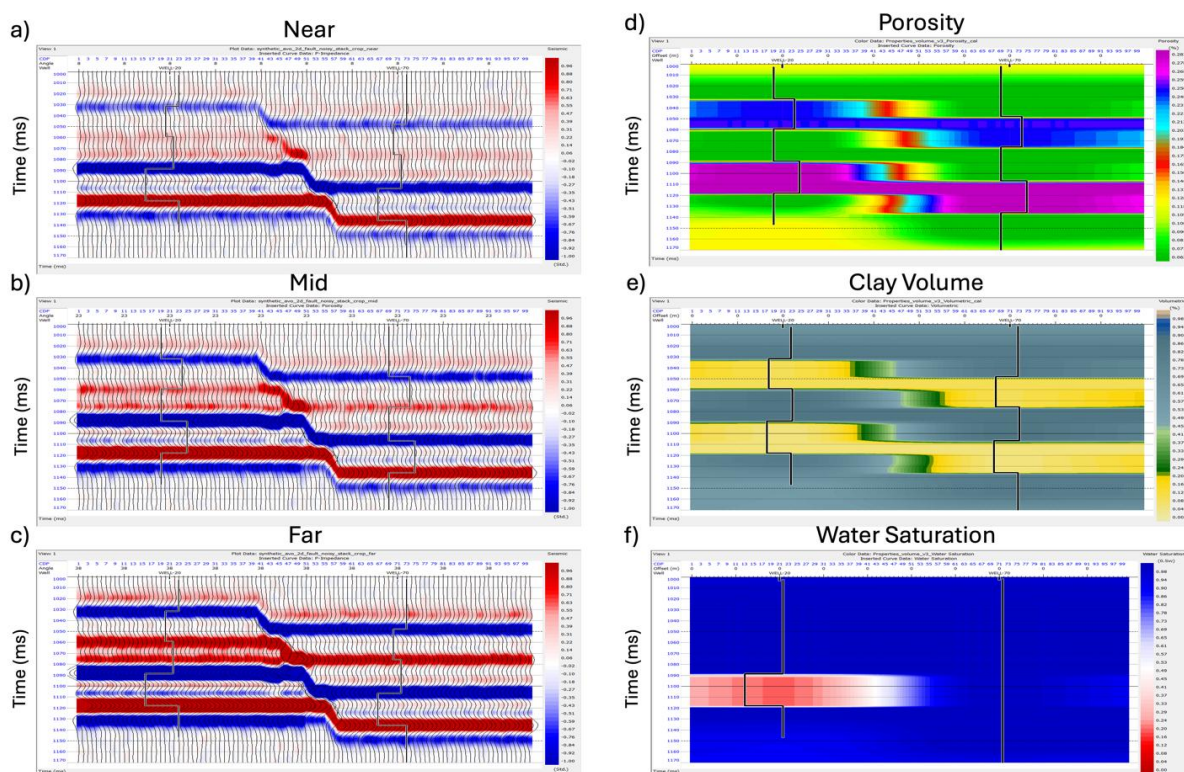


Figure 9.

Seismic partial angle stacks for faulted and noisy model:

(a) Near-angle stack, (b) Mid-angle stack, and (c) Far-angle stack; alongside the corresponding petrophysical sections: (d) Porosity, (e) Clay volume, and (f) Water saturation

The seismic data configuration for this second model is identical to the initial layer-cake model, generated using 100 CDPs across an angle range of 0 to 45 degrees. The 100 CDPs are incorporated to evaluate the BNN's lateral performance, mimicking field-acquired seismic data. Furthermore, the 0 to 45-degree angle range was selected to optimize the BNN process and accurately represent real seismic data, which typically reaches a maximum angle of 45 degrees.

The synthetic seismic data from the second model is subsequently processed into partial angle stacks, which serve as the primary input for the BNN inversion framework (Figure 9). The resulting partial stacks for this complex model exhibit amplitude signatures that are distinctly different from those of the baseline layer-cake model.

Table 3.
Performance evaluation of bnn hyperparameters for faulted and noisy model

	Porosity		Clay volume		Water saturation	
	Well-20	Well-70	Well-20	Well-70	Well-20	Well-70
RMSE	0.078	0.142	0.104	0.156	0.088	0.152
R ² Score	0.815	0.725	0.775	0.685	0.810	0.690
Pearson (r)	0.903	0.851	0.880	0.828	0.900	0.831

The difference is clearly visible from the amplitudes, which are not as neat and sharp as in the first model. The near-angle partial stack results do not show a significant change between the footwall and hanging wall positions. However, the mid- and far-angle partial stack results show a substantial amplitude difference in the footwall area compared to the hanging wall area, especially at the transition from layer three to layer four (Figure 9).

Following the application of the BNN process using parameters identical to those of the first (layer-cake) model, the performance evaluation metrics for the two control wells (Well-20 and Well-70) were derived (Table 3). The analysis of Well-20 reveals a different degree of accuracy compared to the layer-cake model; the predictive errors for the three properties are higher, yielding an average RMSE of 0.09 (a 9% error margin), alongside a reduced correlation characterized by an average R² of 0.8 (an 80% match). Furthermore, the results for Well-70 exhibit a substantially larger error margin, with an average RMSE of 0.15 (15%), and a comparatively lower correlation value with an average R² of 0.7 (70%) when juxtaposed with the Well-20 results (Table 3).

The 1D petrophysical property predictions for the blind-test wells (Well-20 and Well-70) demonstrate the high fidelity and reliability of the proposed Bayesian Neural Network (BNN) framework. As illustrated in Figure 10, the predicted mean curves closely track the actual well logs across the porosity, clay volume, and water saturation profiles. The model successfully reconstructs sharp, blocky lithological transitions such as the abrupt fluid and lithology contrasts observed between 1.75 s and 1.95 s without exhibiting severe smoothing effects. Furthermore, the stochastic nature of the BNN provides robust uncertainty quantification. The true log values consistently fall within the estimated 80% confidence intervals (bounded by the P10 and P90 percentiles), confirming that the model's predictive variance is statistically reliable and successfully avoids overconfidence.

Quantitative evaluation through the prediction residual plots (Figure 10) further validates the stability of the inversion model. The error distributions for all three petrophysical parameters are tightly clustered and symmetrically distributed around the zero-error reference line, indicating an absence of systematic bias in the network's predictions. While minor local spikes in the residuals are observable (e.g., approaching ± 0.1 v/v for clay volume), these deviations are highly localized and exclusively associated with abrupt stratigraphic boundaries where extreme petrophysical contrasts occur. Overall, the minimal and randomly distributed residuals confirm the BNN model's capability to generalize complex subsurface heterogeneities with high precision.

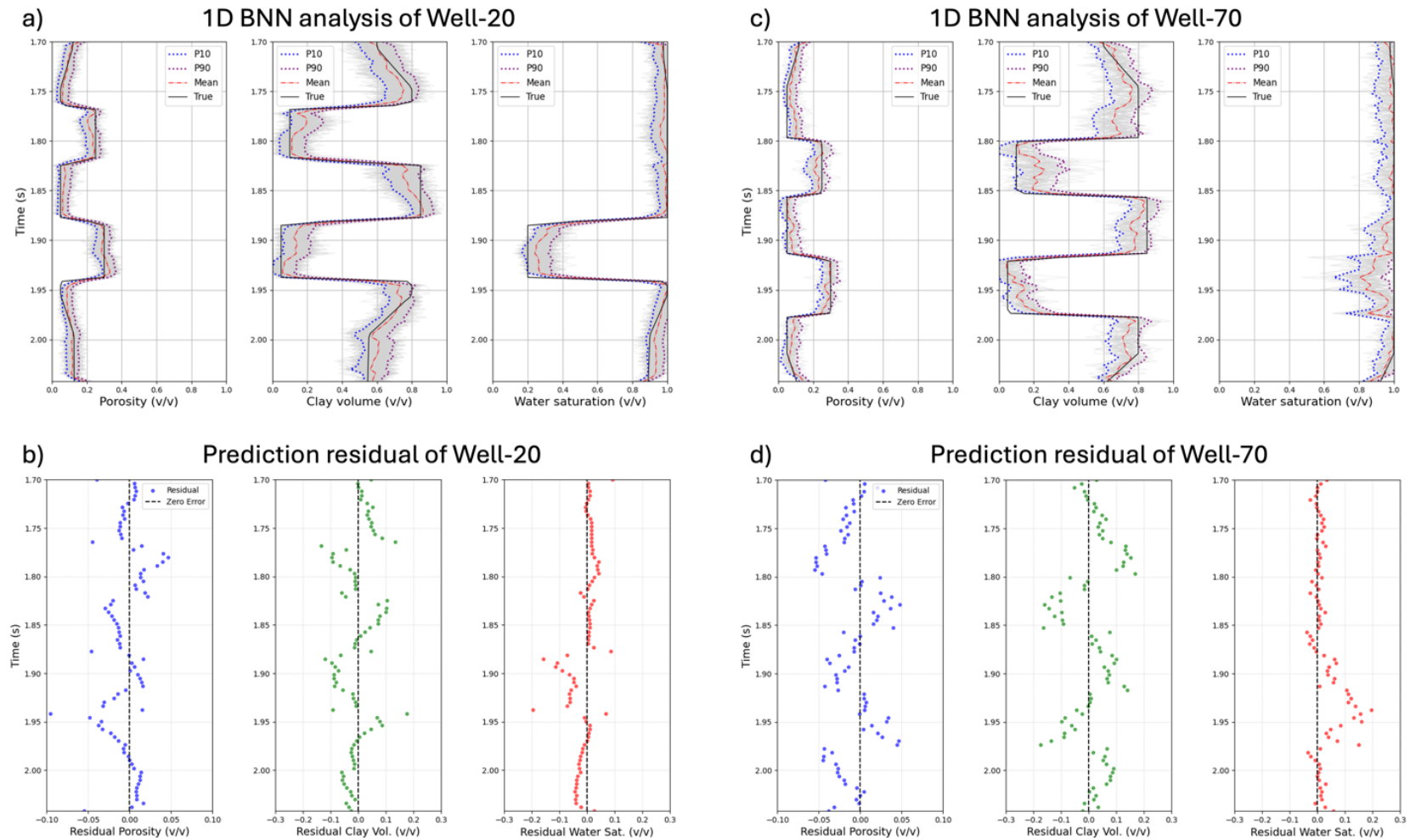


Figure 10.

1D Bayesian Neural Network (BNN) inversion results and the corresponding prediction residuals for faulted and noisy model (a) Petrophysical property predictions (porosity, clay volume, and water saturation) (b) Point plot of the prediction residuals for Well-20 (c) Petrophysical property predictions for Well-70 (d) Point plot of the prediction residuals for Well-70

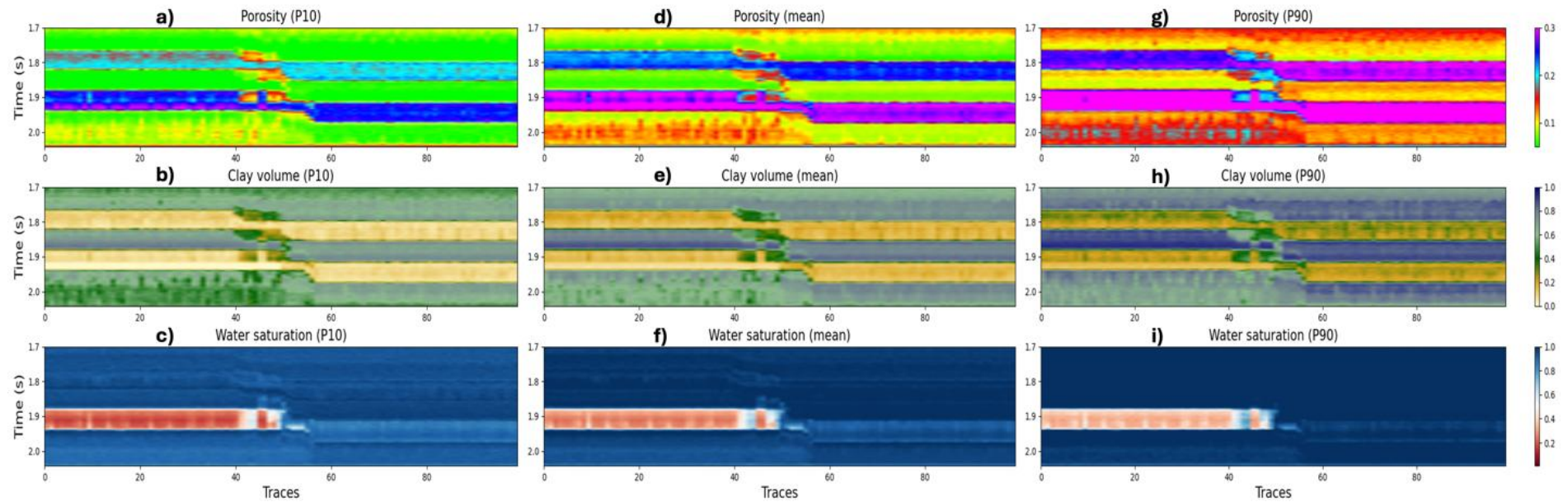


Figure 11.

2D petrophysical sections of a faulted and noisy model generated via BNN inversion, illustrating the P10 stochastic realizations for (a) porosity, (b) clay volume, and (c) water saturation; the mean distributions for (d) porosity, (e) clay volume, and (f) water saturation; and the P90 realizations for (g) porosity, (h) clay volume, and (i) water saturation.

The inclusion of noise and fault structures is hypothesized to be the primary cause for the decreased predictive performance in this second model compared to the layer-cake model. This observation aligns with the findings in (Romero et al., 2025), where the BNN inversion applied to the structurally complex Marmousi model successfully predicted acoustic impedance with high precision. Nevertheless, when applied to real seismic data containing inherent noise in the same study, the prediction results were noticeably inferior to those achieved with the Marmousi or other synthetic models.

The hypothesized degradation of the BNN's predictive performance in the second model incorporating noise and faults is further corroborated by (Li et al., 2024). In that study, petrophysical predictions were conducted using data characterized by noise and structural complexity. The resulting correlation coefficients averaged between 0.7 and 0.8, which is strikingly similar to the findings of our second model. Notably, none of the property predictions in (Li et al., 2024) study achieved a correlation of 0.9. This suggests that, generally speaking, attaining a correlation of 0.9, as observed in the ideal layer-cake model, is highly challenging for the BNN method.

As with the layer-cake model, this second model also produces 2D petrophysical cross-sections (Figure 11). The derived P10, P90, and mean values exhibit geological structural patterns that mirror those of the input partial stack seismic data. Among the three estimated properties, it is evident that the porosity values predicted by the BNN exhibit considerable variation. Consequently, the provided information is more diverse and distinct, as the probabilistic approach yields an ensemble of values rather than a single deterministic output.

While the variability observed in the clay volume and water saturation fields is less pronounced than that of porosity, it nevertheless facilitates a comprehensive probabilistic assessment of in-place hydrocarbon volumes (Figure 11). These varied in-place estimates critically influence the economic viability analysis of a hydrocarbon field. Consequently, production and drilling expenditures can be robustly forecasted, effectively mitigating the economic risks associated with subsequent production phases and overall field development strategies.

In addition to evaluating the BNN framework across two distinct geological models, a comparative analysis was performed against a conventional deterministic model-based inversion. The visual comparison, presented in Figure 12, highlights diverging spatial patterns between the two approaches, most notably in proximity to the fault zone. The BNN predictions exhibit localized discrepancies within the near-fault regions. This artifact arises because the porosity cross-section utilized as training data (Figure 12) does not yet structurally align with the inherent fault trends delineated in the seismic data.

To mitigate these discrepancies, the property model should be constrained using interpreted seismic horizons. Conversely, the deterministic inversion results display clearly defined fault patterns that align with geological concepts, as this model is inherently constrained by seismic horizons. Nevertheless, regarding the absolute porosity values, the BNN-derived porosity cross-section demonstrates a higher degree of accuracy than the deterministic method. This improvement is particularly evident in the second layer, a water-bearing sandstone interval. In this layer, the deterministic method underestimates the porosity compared to the actual data, whereas the BNN outputs accurately reflect the predefined values in Table 1.

The underestimated porosity values observed in the deterministic inversion results can be largely attributed to the conversion process. In the deterministic approach, the porosity cross-section is derived by converting acoustic impedance values into porosity. This conversion relies on establishing a linear relationship between the porosity and the acoustic impedance generated by the deterministic inversion. Consequently, the accuracy of the conversion heavily depends on this linear correlation; a strong correlation yields high accuracy, whereas a weak correlation results in an inaccurate or mismatched porosity cross-section.

Deterministic inversion yields only a single output without providing any quantification of uncertainty. Conversely, the probabilistic approach generates an ensemble of values, rendering its results more advantageous than deterministic methods. This probabilistic approach, coupled with uncertainty estimation, is highly essential for field development. Economic evaluations derived from probabilistic outputs offer a wider range of scenarios, delivering critical information regarding the minimum and maximum economic potential of a field. Consequently, the BNN method serves as an excellent solution for implementing seismic inversion in field development projects.

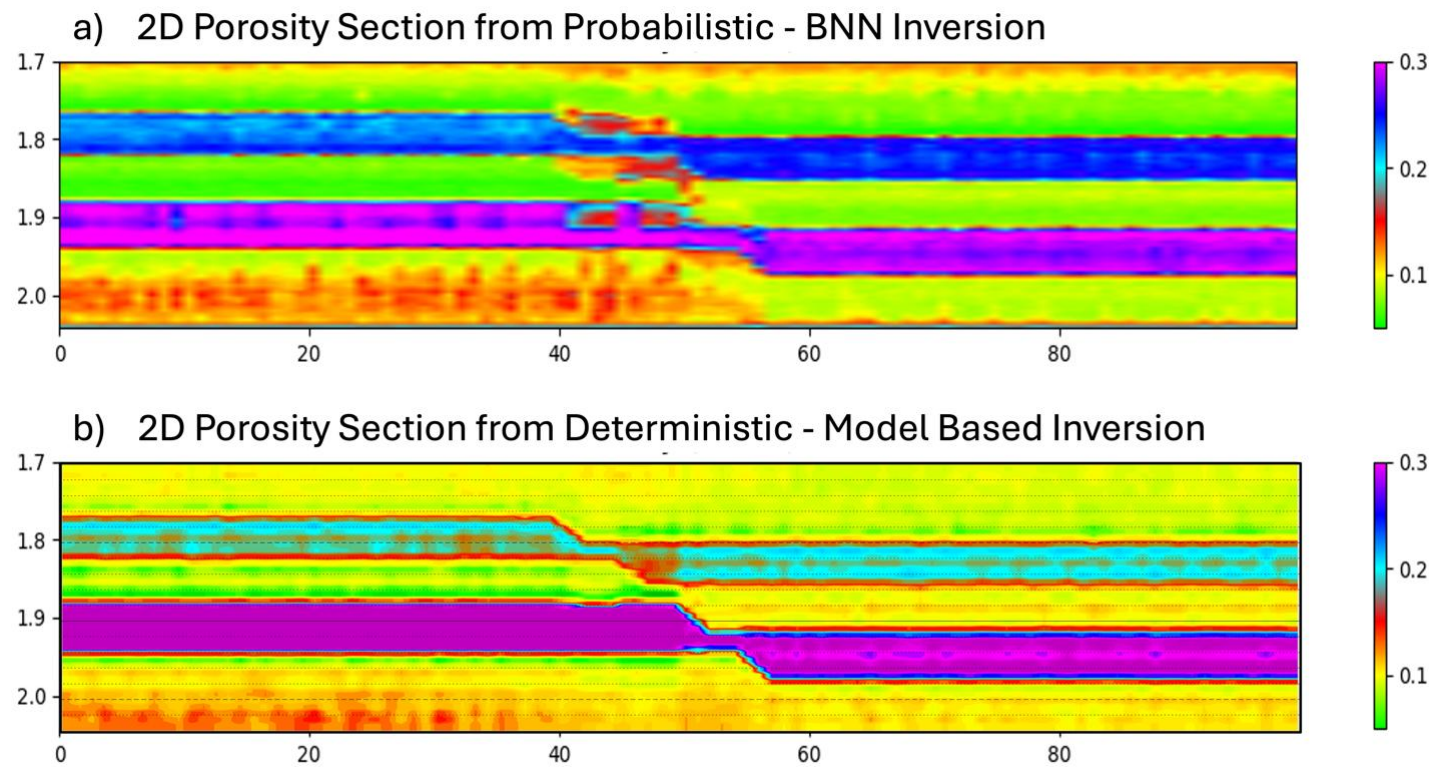


Figure 12.
Comparison of porosity cross-sections derived from: (a) BNN probabilistic inversion, and (b) model-based deterministic inversion.

4. Conclusion

The probabilistic inversion process utilizing BNN has been successfully executed on the synthetic seismic data. The outputs derived from this inversion include key petrophysical properties: porosity, clay volume, and water saturation. By leveraging these properties, the characteristics of gas-saturated sandstone reservoirs can be effectively differentiated from those of water-bearing reservoirs. Additionally, this BNN inversion generates an ensemble of values, enabling the probabilistic calculation of the 10th percentile (P10), the 90th percentile (P90), and the mean value across all model outputs. Among the derived probabilistic distributions, the mean realization exhibits the highest fidelity to the ground-truth data, rendering it directly applicable for deterministic reservoir characterization. However, within the context of field development, boundary percentiles such as P10 and P90 are frequently employed to quantify the uncertainty associated with hydrocarbon resource estimation. Crucially, this probabilistic envelope provides a direct solution to the non-uniqueness problem inherent in seismic inversion. In complex geological settings where multiple varying petrophysical combinations yield identical seismic responses, deterministic models fail by forcing a single, potentially biased estimate.

In contrast, the BNN explicitly captures and maps this ambiguity. A wide interval between the P10 and P90 boundaries serves as a quantitative diagnostic tool, explicitly flagging zones of high geological heterogeneity and strong non-uniqueness. Conversely, a narrow envelope indicates regions of high predictive confidence. Therefore, the BNN framework solves the non-uniqueness problem not by eliminating it, but by accurately quantifying the full range of plausible geological scenarios.

The probabilistic BNN inversion framework has demonstrated considerable success in characterizing gas-saturated sandstone reservoirs. Nonetheless, further investigation into the practical deployment of this method is essential, fundamentally requiring the integration of field-acquired seismic and well log data. While adapting this methodology for alternative reservoir typologies is highly promising, it necessitates rigorous subsequent studies to adequately address their contrasting petrophysical and geological characteristics.

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6. Declarations

6.1 Author contributions

Edi Sanjaya served as the principal investigator, conceptualized the research, and oversaw the overall project administration. Praditiyo Riyadi was responsible for data processing, preparing the original draft, as well as reviewing and editing the manuscript. Fadhlur Rahman was involved in data processing and the structural editing of the manuscript.

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6.3 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.

6.4 The use of AI or AI-assisted technologies

During the preparation of this work, the authors used artificial intelligence (AI) tools to assist with the script development and debugging of the Python programming codes. Furthermore, AI was employed for language editing, grammar checking, and manuscript formatting. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the scientific content, interpretation, and conclusions of the publication.

7. Glossary of terms & symbols

Terms & symbols	Definition	Unit
V _p	Compressional (P-wave) velocity	km/s or m/s
V _s	Shear-wave velocity	km/s or m/s
ϕ	Total porosity fraction	fraction, % or v/v
V _{cl}	Clay volume fraction	fraction or v/v
ρ	Bulk density	g/cc
ρ_{ma}	Rock matrix density	g/cc
ρ_{quartz}	Density of quartz minerals	g/cc
ρ_{clay}	Density of clay minerals	g/cc
ρ_{fl}	Fluid density in the rock	g/cc
Sw	Water saturation	fraction, % or v/v
ρ_{water}	Water density	g/cc
ρ_{hc}	Hydrocarbon density	g/cc
ρ_{bulk}	Bulk density (function of pore fluid and solid rock matrix densities)	g/cc
R θ	Angle-dependent reflection coefficient	-
R0	Amplitude Variation with Angle (AVA) intercept	-
G	Amplitude Variation with Angle (AVA) gradient	-
θ	Angle of incidence	°
P(m d)	Posterior probability distribution of the model parameters	-
P(m)	Prior model probability distribution	-
P(d m)	Data likelihood function	-
P(d)	Marginal likelihood of the data (evidence)	-
Pa	Acceptance probability in Metropolis-Hastings algorithm	-
m _i	Current model (current state)	-
m'	Newly proposed model (proposed state)	-
g	Proposal distribution (MCMC) / Non-linear activation function	-
f	Deterministic rock physics forward modeling operator	-
z	Hidden states in neural network	-
w	Trainable weight matrices	-
b	Bias vectors	-
σ^2	Variance characterizing the uncertainty or noise of the measurement	-
α	User-defined hyperparameter weight controlling well log constraint strictness	-
L _{total}	Overall loss value optimized by the network	-
L _{property}	Data-driven property loss function	-
Em	Expected value (predictive mean) of petrophysical properties	-
NMC	Total number of Monte Carlo simulation iterations	-
mk	Stochastic property vector output generated at the k-th iteration	-
N	Total number of spatial seismic traces in a single training batch	-
N _t	Total number of temporal samples per trace	-

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