

PHYSICS-GUIDED POROELASTIC FORWARD MODELING FOR FLUID-SENSITIVE RESERVOIR CHARACTERIZATION

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ABSTRACT

Reliable discrimination of interstitial fluids from seismic data requires a modeling framework that preserves the physical relationships between porosity, mineral composition, fluid properties, elastic moduli, and seismic amplitudes. This study presents a physics-guided poroelastic forward modeling workflow in which three-dimensional porosity realizations generated by sequential Gaussian simulation (SGS) are propagated through a neural network prediction step constrained by rock physics relationships. The framework combines elastic constitutive equations, the Gassmann fluid substitution, a critical-porosity description of dry-frame stiffness, and rock-physics calibration data to predict the saturated bulk modulus, shear modulus, and density of pore spaces filled with gas, oil, and water. The predicted elastic parameters are converted into compressional- and shear-wave velocities as well as fluid-sensitive attributes, including acoustic impedance, $\lambda\rho$, $\mu\rho$, V_p/V_s , and Poisson's ratio-based indicators. The pre-stack synthetic seismic responses are then generated using an Aki–Richards reflectivity approximation, Ricker wavelets at representative frequencies of 24, 44, and 64 Hz, and controlled coherent noise. The model reproduces the expected physical order of fluid responses: gas produces the softest response, controlled by the lowest fluid bulk modulus, and the strongest near-offset AVO signature, while oil and water progressively increase the effective bulk modulus. The reported calibration correlations are 0.912 for V_p , 0.801 for V_s , and 0.890 for density. Synthetic reflection coefficients of approximately 0.18, 0.10, and 0.04 for gas, oil, and water, respectively, demonstrate a clear separation of fluids within the modeled domain. The results indicate that the combination of stochastic porosity modeling, physics-driven learning, and seismic forward modeling provides an interpretable basis for the characterization of fluid-sensitive reservoirs and for subsequent hybrid seismic inversion.

Keywords: physics-based learning, poroelastic modelling, Gassmann fluid substitution, AVO, synthetic seismic data, reservoir characterization, seismic inversion.

INTRODUCTION

Quantitative reservoir characterization aims to convert seismic observations into physically meaningful descriptions of lithology, porosity, and pore conditions. This task is challenging because seismic amplitudes are simultaneously controlled by density, elastic stiffness, stratigraphic architecture, pore geometry, and fluid properties. Consequently, a seismic response consistent with multiple geological models may not uniquely identify the fluid state. Integrated reservoir characterization workflows are therefore necessary to combine geological, petrophysical, and geophysical information rather than relying on a single seismic attribute [1]. Fluid discrimination depends particularly on the sensitivity of compressional properties to the elastic modulus of the interstitial fluid. Conventional AVO analysis commonly uses combinations of intercept, gradient, and fluid-sensitive elastic parameters such as $\lambda\rho$ and $\mu\rho$ to separate fluid effects from lithological effects [2]. However, the inverse problem is not unique and becomes increasingly ill-conditioned when well-log data are sparse, seismic bandwidth is limited, or the reservoir contains more than one type of fluid.

Machine learning methods have recently become important in seismic inversion because they can learn nonlinear relationships between seismic measurements and subsurface properties [3], [4]. Deep neural networks have been applied to impedance inversion, pre-stack inversion, and the prediction of petrophysical properties, including in Block F3 in the Dutch North Sea [11-13],[25],[30]. Nevertheless, purely data-driven networks can produce predictions that match the training data while violating known constraints of rock physics. This limitation has led to the development of constrained and physics-guided learning strategies, in which the network is regularized by governing equations or constitutive relations [5],[7].

Rock physics provides the physical link between the reservoir state and the seismic response. The elastic properties of saturated rocks depend on dry stiffness, mineral properties, porosity, and fluid composition. Gassmann's theory remains one of the primary frameworks for relating the moduli of dry rock to those of the saturated medium under its underlying low-frequency assumptions [18],[21]. The properties of interstitial fluids, in turn, exert a strong influence on seismic velocities and amplitudes [19], while AVO formulations provide a practical bridge between elastic contrasts and angle-dependent reflection coefficients [9],[10].

The objective of this work is therefore to develop an interpretable forward modeling workflow that combines (i) three-dimensional porosity simulations based on the SGS model, (ii) physics-driven prediction of poroelastic properties, (iii) Gassmann fluid substitution and critical porosity constraints, and (iv) angle-dependent synthetic seismic modeling. The specific objective is to quantify how gas, oil, and water saturation modify elastic properties and their seismic expression. The resulting synthetic domain is intended to support subsequent hybrid seismic inversion while maintaining an explicit physical interpretation of the learned relationships.

MATERIALS AND METHODS

Overall modelling strategy

The workflow is organized as a sequential forward operator. First, SGS is used to generate three-dimensional porosity realizations that preserve the spatial variability implied by the available geological and well data. Such stochastic models are useful for extending the spatial coverage of sparse observations while maintaining realistic heterogeneity. The porosity volume

is then fed into a physics-driven neural network model that predicts elastic properties under various interstitial fluid conditions. The predicted dry and saturated properties are validated against rock physics relationships before being transformed into seismic attributes and pre-stack synthetic responses. This architecture follows the general trend toward integrating geostatistics, rock physics, and machine learning for reservoir characterization [1],[17],[25],[26].

Poroelastic and elastic formulation

Under the isotropic-elastic low-strain approximation used in this modeling framework, the stress tensor is related to the strain through the stiffness tensor:

$$\sigma_{ij} = C_{ijkl} \cdot \epsilon_{kl} \quad (1)$$

where σ_{ij} is the stress tensor, ϵ_{kl} is the strain tensor, and C_{ijkl} is the fourth-order elastic stiffness tensor. The corresponding displacement field obeys the elastic equation of motion, which provides the physical basis for wave propagation and for the constraints imposed on the learning stage:

$$\nabla^2 \mathbf{u} - \left(\frac{1}{v^2} \right) \cdot \frac{\partial^2 \mathbf{u}}{\partial t^2} = 0 \quad (2)$$

For an isotropic medium, the bulk modulus K , the shear modulus G , and the bulk density ρ are converted to seismic velocities according to:

$$V_p = \sqrt{\frac{K + \frac{4}{3}G}{\rho_{\text{bulk}}}}, \quad V_s = \sqrt{\frac{G}{\rho_{\text{bulk}}}} \quad (3)$$

These equations are used as physical constraints rather than as a full-fledged numerical wave solver. The formulation is consistent with the role of constitutive physics in physics-guided inversion [5],[7] and with the standard relationships in rock physics [18].

Physics-guided neural prediction and loss function

The neural layer receives the SGS porosity results as well as the parameters defining the mineral matrix and the pore fluid. Its outputs are saturated elastic properties, primarily K_{sat} , G_{sat} , and ρ_{sat} . To avoid treating the network as an unconstrained black box, the objective function combines a data term with a physical regularization term:

$$L_{\text{Total}} = L_{\text{Data}} + \lambda L_{\text{Phys}} \quad (4)$$

The data term measures the deviation between the predicted targets and the calibration targets defined in next section, while the physics term penalizes deviations from the expected Gassmann fluid-substitution trends and from the dry-rock frame stiffness. In general form:

$$L_{\text{Data}} = \frac{1}{N} \sum_{i=1}^N \sum_{k=1}^P (y_{i,k} - \hat{y}_{i,k})^2 \quad (5)$$

The physical penalty is derived from the difference between the predicted saturated bulk modulus and the Gassmann-consistent value, as well as a penalty on the dry-rock frame stiffness that enforces the prescribed critical-porosity trend (Eq. 6). The coefficient λ controls the balance between empirical calibration and physical consistency. It has been shown that deep learning strategies with physical constraints of this type improve interpretability and reduce physically unrealistic inversion solutions [5],[7],[22].

$$L_{\text{Phys}} = \frac{1}{N} \sum_{i=1}^N \left[(K_{\text{sat},i} - K_{\text{sat},i}^{\text{Gass}})^2 + (K_{\text{dry},i} - K_{\text{dry},i}^{\text{CP}})^2 + (G_{\text{dry},i} - G_{\text{dry},i}^{\text{CP}})^2 \right] \quad (6)$$

where the superscripts Gass and CP denote the values given by Gassmann's relation (Eq. 7) and by the critical-porosity dry-frame model (Eq. 8), respectively, evaluated with the predicted density-consistent inputs of each sample. All moduli are normalized by the mineral moduli before computing the loss so that the three terms have comparable magnitudes.

Network architecture and training

The physics-guided predictor is a two-stage fully connected network implemented in Python with TensorFlow and Keras. The first stage predicts K_{sat} , G_{sat} and ρ_{sat} from the SGS porosity and the mineral and fluid parameters (ϕ , K_{min} , G_{min} , ρ_{min} , K_{fl} , ρ_{fl}), standardized by z-score normalization; the second stage evaluates Gassmann's equations and the critical-porosity relations (Eqs. 7–8), which provide the reference values of the physics term in Eq. (6). Training uses the Adam optimizer with a fixed learning rate of 0.001, a batch size of 16 and a maximum of 50 epochs, with an EarlyStopping callback on the validation loss and L2 weight regularization to prevent overfitting. Hyperparameters, including the regularization weight λ of Eq. (4), were selected by grid search on the validation subset. The first stage consists of five hidden fully connected (dense) layers of 600, 400, 200, 100 and 64 neurons, respectively, all using the ReLU activation function, followed by a linear output layer of three neurons (K_{sat} , G_{sat} and ρ_{sat}). Although λ was selected through this exhaustive search, the present study does not report a single optimal value of λ , nor a quantitative comparison with an unconstrained network ($\lambda = 0$); this comparison was not performed within the scope of this work. In the current workflow, the role of the physics term is justified by the explicit Gassmann and critical-porosity constraints, which restrict the space of admissible solutions, and by published results on physics-constrained learning [5],[7],[22]. A systematic sensitivity analysis of λ and a direct comparison with an unconstrained network are nevertheless important and will be addressed in a future study.

Fluid substitution and rock-physics parameterization

Fluid substitution was evaluated for gas, oil, and water. The ranges adopted are those summarized in Table 1. The rock structure is characterized by ranges of mineral bulk modulus, shear modulus, and density representative of the modeled reservoir system. A critical porosity of 35% was used to control the evolution of dry stiffness.

Table 1. Parameter ranges used for fluid substitution and poroelastic modelling.

Parameter	Gas	Oil	Water	Mineral / dry-frame
K_{fluid} (GPa)	0.1–0.4	0.4–3.0	2.0–4.0	–
ρ_{fluid} (g/cm ³)	0.1–0.5	0.7–1.1	0.9–1.2	–
K_{mineral} (GPa)	–	–	–	36.7–39.9
G_{mineral} (GPa)	–	–	–	44–45
ρ_{mineral} (g/cm ³)	–	–	–	2.65–2.76
Critical porosity, ϕ_c	–	–	–	35%

Gassmann's substitution is used to estimate the saturated bulk modulus based on the dry matrix modulus, the mineral bulk modulus, the porosity, and the fluid bulk modulus [20],[21]. The shear modulus is retained according to the low-frequency fluid substitution assumption, while

the density is updated from the solid and pore-fluid volume fractions (Eqs. 7-9). The resulting elastic properties are transformed into fluid-sensitive indicators, including acoustic impedance $I_p = \rho V_p$, $\lambda\rho$, and $\mu\rho$, as well as V_p/V_s , Poisson's ratio and Poisson impedance [2],[18].

In explicit form, the saturated moduli are obtained from Gassmann's equations [20],[21]:

$$K_{\text{sat}} = K_{\text{dry}} + \frac{\left(1 - \frac{K_{\text{dry}}}{K_{\text{min}}}\right)^2}{\frac{\phi}{K_{\text{fl}}} + \frac{1 - \phi}{K_{\text{min}}} - \frac{K_{\text{dry}}}{K_{\text{min}}^2}}, \quad G_{\text{sat}} = G_{\text{dry}} \quad (7)$$

The dry-frame moduli follow the critical-porosity model, in which stiffness decreases linearly from the mineral value at zero porosity to zero at ϕ_c [18]:

$$K_{\text{dry}} = K_{\text{min}} \left(1 - \frac{\phi}{\phi_c}\right), \quad G_{\text{dry}} = G_{\text{min}} \left(1 - \frac{\phi}{\phi_c}\right), \quad 0 \leq \phi < \phi_c \quad (8)$$

and the bulk density of the saturated rock is computed from the solid and pore-fluid volume fractions:

$$\rho_{\text{sat}} = (1 - \phi)\rho_{\text{min}} + \phi\rho_{\text{fl}} \quad (9)$$

where K_{dry} and G_{dry} are the dry-frame moduli, K_{min} , G_{min} and ρ_{min} are the mineral properties, K_{fl} and ρ_{fl} are the pore-fluid properties (Table 1), ϕ is the porosity and $\phi_c = 0.35$ is the critical porosity. Eqs. (7)-(9) provide the reference values used in the physics term of Eq. (6).

Synthetic seismic forward modelling

The final modeling step converts the elastic property values into angle-dependent seismic responses. For pre-critical incidence angles, the P-P reflection coefficient is approximated using the Aki-Richards formulation, which provides an effective representation of how the reflection amplitude depends on contrasts in V_p , V_s , density, and incidence angle [9],[10]:

$$R_{\text{PP}}(\theta) \approx \frac{1}{2} \left(1 - 4 \left(\frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta\rho}{\rho} + \frac{1}{2 \cos^2 \theta} \frac{\Delta V_p}{V_p} - 4 \left(\frac{V_s}{V_p} \right)^2 \sin^2 \theta \frac{\Delta V_s}{V_s} \quad (10)$$

where θ is the average angle of incidence and $\Delta V_p/V_p$, $\Delta V_s/V_s$ and $\Delta\rho/\rho$ are the relative contrasts across the reservoir interface. For incidence angles up to 30° , Eq. (10) reduces to the two-term form $R_{\text{PP}}(\theta) \approx A + B \sin^2 \theta$, with intercept $A = \frac{1}{2}(\Delta V_p/V_p + \Delta\rho/\rho)$ and gradient $B = \frac{1}{2}\Delta V_p/V_p - 2(V_s/V_p)^2(\Delta\rho/\rho + 2\Delta V_s/V_s)$ [9]; A and B are estimated by least-squares fitting of the synthetic amplitudes over $0-30^\circ$ and are used in Section "intercept-gradient discrimination". The synthetic trace is then obtained by convolution with a source wavelet:

$$D_{\text{sim}}(\theta, t) = R_{\text{pp}}(\theta, t) * w(\theta, t) + N(t) \quad (11)$$

where $*$ denotes temporal convolution, $w(\theta, t)$ is the Ricker wavelet and $N(t)$ is the additive noise term.

Ricker wavelets with dominant frequencies of 24, 44, and 64 Hz were used to represent band-limited seismic sources. Figure 1 shows the Ricker wavelet and its representative angle-dependent response for the three dominant frequencies considered (24, 44 and 64 Hz). Incidence angles ranging from 0° to 30° were considered. Controlled coherent noise was added to mimic the imperfections in the acquired seismic data. The noise $N(t)$ is a coherent component added to reproduce realistic acquisition conditions and the band-limited character (10–60 Hz) of the field data.

The use of multiple frequency bands and angular partitions is consistent with current pre-stack inversion strategies that seek to exploit complementary seismic attributes [11],[13],[23],[24].

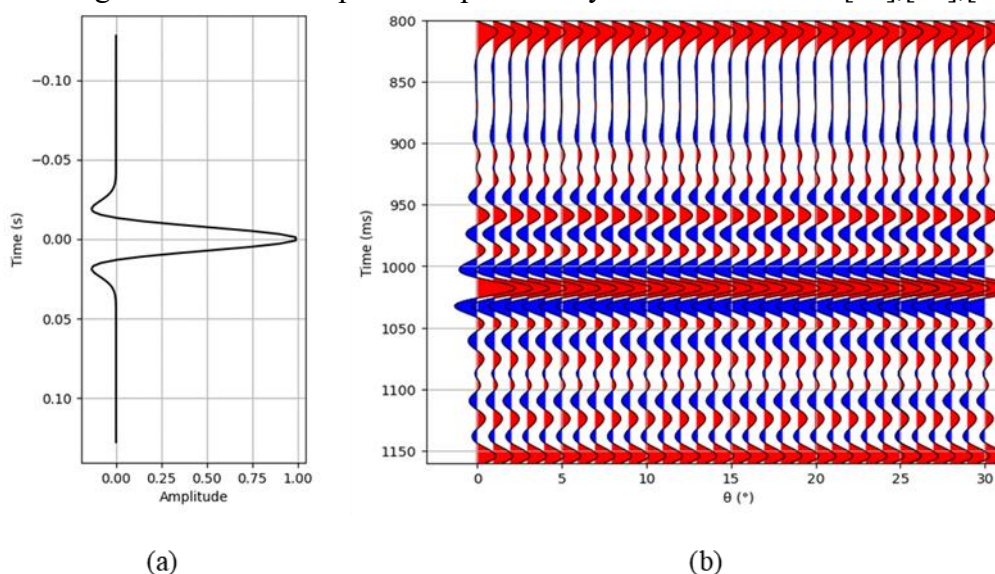


Figure 1. Ricker wavelet and representative angle-dependent wavelet response used in the synthetic seismic forward model. The three dominant frequencies considered in the study are 24, 44 and 64 Hz.

EXPERIMENTAL DATA AND MODELLING CONFIGURATION

The modeling domain consists of structured three-dimensional reservoir grids populated with SGS porosity realizations. The stochastic porosity volumes provide the spatial prior for the neural network prediction step and allow the forward model to represent inter-well heterogeneity rather than restricting the learning problem to individual well trajectories. This strategy is consistent with previous seismic and geostatistical studies of Block F3, where seismic inversion and geostatistical methods were used to estimate the properties of subsurface rocks [25],[26].

Three interstitial fluid scenarios were considered: gas, oil, and water. The ranges of the modeled fluid properties are: $K_{\text{fluid}} = 0.1\text{--}0.4$ GPa and $\rho_{\text{fluid}} = 0.1\text{--}0.5$ g/cm³ for gas; $K_{\text{fluid}} = 0.4\text{--}3.0$ GPa and $\rho_{\text{fluid}} = 0.7\text{--}1.1$ g/cm³ for oil; and $K_{\text{fluid}} = 2.0\text{--}4.0$ GPa and $\rho_{\text{fluid}} = 0.9\text{--}1.2$ g/cm³ for water. The mineral properties were allowed to vary within the following limits: $K_{\text{mineral}} = 36.7\text{--}39.9$ GPa, $G_{\text{mineral}} = 44\text{--}45$ GPa, and $\rho_{\text{mineral}} = 2.65\text{--}2.76$ g/cm³. The critical porosity was set at 35%.

The seismic response was evaluated for incidence angles ranging from 0° to 30° and at representative frequency bands of 24, 44, and 64 Hz. These parameters were selected to examine how fluid-dependent elastic contrasts survive the limited temporal bandwidth of realistic seismic observations. The resulting synthetic domain provides a controlled basis for testing fluid-sensitive inversion methods, including neural network and ensemble approaches [29],[30].

Origin and size of the datasets

The study uses the public 3D seismic survey of Block F3 in the Dutch Central Graben, North Sea, which covers approximately 384 km² with a record length of 1848 ms, a sampling interval of 4 ms and a bin size of 25 m [25–28]. Seven major seismic horizons were interpreted in OpendTect, and the two horizons bounding the porous deltaic sandstone reservoir (porosity of

16–35%) define the target interval. Logs from four vertical wells, including F03-4 (gamma ray, bulk density, porosity, sonic velocity and acoustic impedance), condition the SGS porosity realizations. These are generated on a terrain-conforming structured grid built with the PyVista StructuredGrid class, after quality control of the porosity logs (declustering, smoothing and depth alignment), normal-score transformation, variogram modelling and collocated cokriging with the interpreted horizons. The calibration targets referred to in Sections “Physics-guided neural prediction and loss function” and “Elastic response to porosity and fluid properties” are the measured V_p , V_s and density logs of these wells, so that the correlation coefficients reported in the last section quantify the agreement between the rock-physics forward model and the well data. The forward-modelled dataset comprises $N = 530,600$ samples, which were divided by stratified random sampling into training (75%), validation (15%) and test (10%) subsets; a five-fold cross-validation was additionally applied to check the stability of the results.

RESULTS

Elastic response to porosity and fluid properties

The model reproduces the expected dependence of seismic velocity on porosity and fluid bulk modulus (Figure 2). For all three fluid classes, an increase in porosity produces a systematic reduction in both V_p and V_s because the effective rock frame becomes more compliant. At a fixed porosity, an increase in the fluid bulk modulus increases the compressional response, with the highest velocities associated with the water-saturated case, intermediate values for oil, and the lowest values for gas. This order is consistent with the established sensitivity of seismic properties to the compressibility of the interstitial fluid [19],[21].

The calibration results reported for the model against the measured well logs (Section “experimental data”) are a correlation coefficient of 0.912 for V_p , 0.801 for V_s , and 0.890 for density, with root-mean-square errors of 32.54 m/s for V_p and 22.72 m/s for V_s . These values indicate that the forward model reproduces the main trends in the calibration data and provides a physically consistent target space for the subsequent inversion. The weaker correlation for V_s compared to V_p is consistent with the greater sensitivity of shear properties to frame stiffness and, consequently, to uncertainties in porosity and the parameterization of dry rock.

Fluid-dependent seismic amplitudes and AVO response

The synthetic near-offset traces and reflection coefficients show a clear distinction among the three fluid cases (Figure 3). Gas produces the largest near-offset response, oil is intermediate, and water produces the smallest amplitude. The modeled reflection coefficients are approximately 0.18 for gas, 0.10 for oil, and 0.04 for water in the representative near-angle configuration. These differences stem primarily from the significant reduction in the effective bulk modulus associated with gas compared to oil and water, which alters the V_p and acoustic impedance at the reservoir boundary.

The AVO curves also show that the fluid classes remain separable as the angle of incidence increases. Gas exhibits the steepest increase in R_{PP} , oil has an intermediate gradient, and water has the shallowest gradient. This behavior is consistent with the use of intercept–gradient analysis for fluid discrimination [2],[9],[10]. The result also supports the use of angle-dependent inputs in machine learning inversion, as the fluid classes follow distinct trajectories in synthetic AVO space [11],[12].

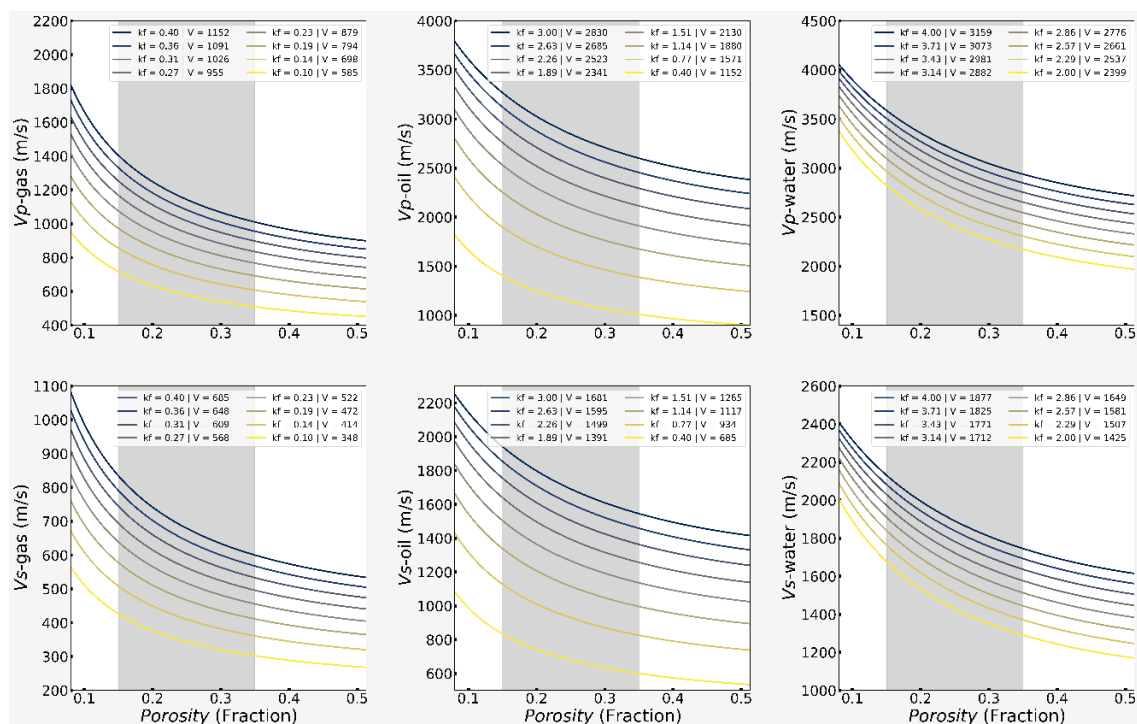


Figure 2. Modelled compressional and shear velocities as functions of porosity for gas-filled, oil-filled and water-filled pore spaces. The curves show the systematic reduction of velocity with increasing porosity and the increase in velocity with fluid bulk modulus.

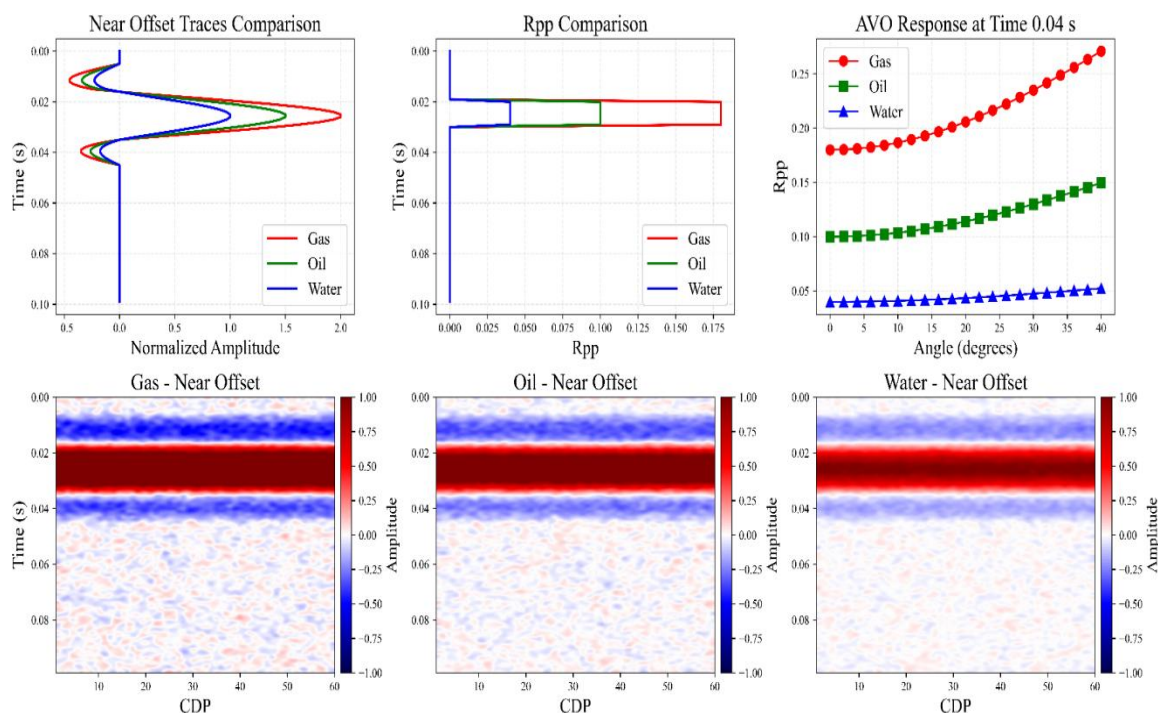


Figure 3. Synthetic near-offset traces, P - P reflection coefficients and AVO response for gas, oil and water. Gas exhibits the largest near-offset amplitude and strongest angle-dependent response, whereas water produces the weakest response.

Intercept-gradient discrimination

Intercept-gradient cross-plots (gradient B versus intercept A) provide an additional perspective on the separability of the fluids (Figure 4). Each fluid case exhibits a highly consistent linear trend with a negative slope. The reported correlation coefficients are approximately -1.000 for gas, -0.999 for oil, and -0.998 for water, indicating that the synthetic responses are internally consistent and highly structured. When the three fluids are combined, the trends remain distinct, with gas occupying the widest gradient range, oil an intermediate range, and water the narrowest range. The separation is therefore not based solely on a single amplitude level, but on the combined behavior of the intercept and the gradient.

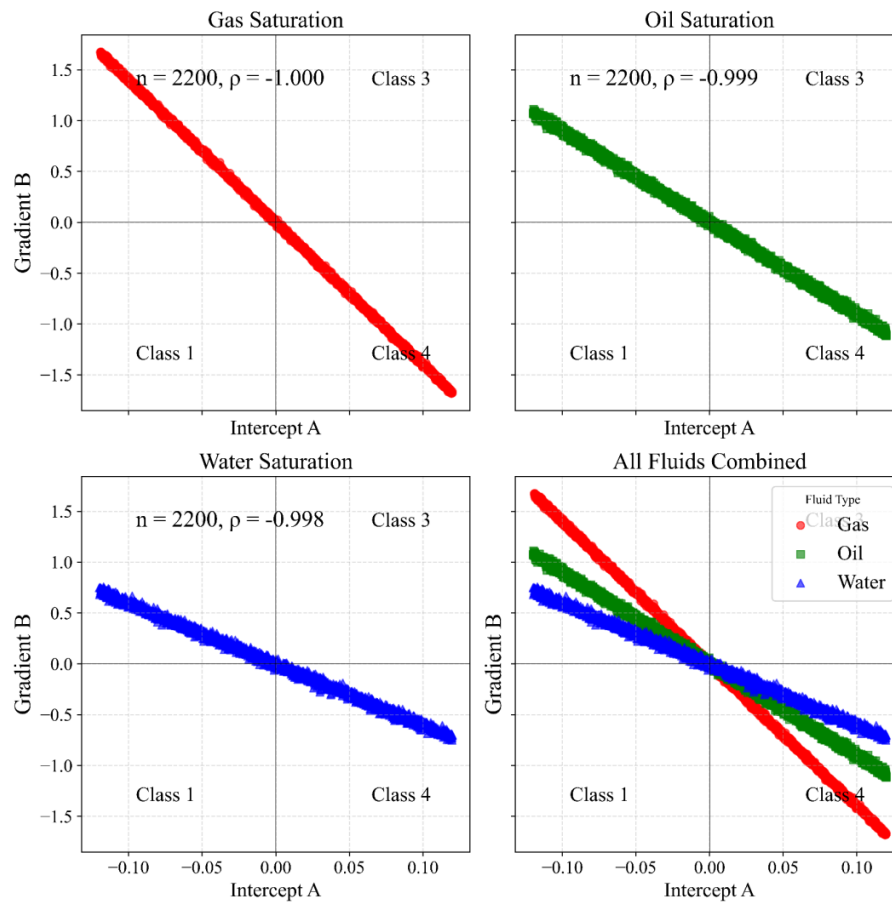


Figure 4. Intercept–gradient cross-plots for gas, oil and water saturation and for the combined fluid population. The distinct trends demonstrate the potential of AVO attributes for fluid discrimination in the synthetic domain.

The near-perfect intercept–gradient correlations require clarification. For each fluid class, A and B are linear combinations of the same relative contrasts $\Delta V_p/V_p$, $\Delta V_s/V_s$ and $\Delta \rho/\rho$ at a single reservoir interface (Eq. 10), and within a given fluid class these contrasts are driven almost exclusively by one variable, porosity, through the critical-porosity frame model (Eq. 8). A and B are therefore nearly collinear by construction. The coherent noise $N(t)$ is added to the traces and not to the elastic parameters; because A and B are estimated by least-squares fitting over all angles between 0° and 30° , the noise is largely averaged out, and its residual effect on A and B is small compared with the porosity-driven variation. These correlations should therefore be

regarded as an upper bound reflecting the idealized synthetic setting; with field data, lithological heterogeneity, tuning, residual moveout and incoherent noise are expected to reduce them substantially.

DISCUSSIONS

The main strength of the proposed framework is the explicit coupling of machine learning with physical constraints. Data-driven inversion methods can be highly effective when the training data accurately represent the target domain, but their predictions can become unstable when the test domain differs from the training distribution [3],[4],[13],[14]. In the current workflow, the network is not required to learn an unrestricted mapping between porosity and elastic properties. Instead, its outputs are constrained by elastic relationships, the Gassmann substitution, and critical porosity behavior. This reduces the physically admissible solution space and improves interpretability [5],[7].

SGS porosity realizations are also important because they provide spatially distributed training support. Geostatistical simulation can propagate well data away from control points while preserving heterogeneity and uncertainty [17],[25],[26]. This is particularly useful in reservoirs where the number of wells is low relative to the seismic sampling density. The resulting elastic volumes can then be sampled consistently with seismic traces, angles, and frequency bands.

The fluid response observed in the synthetic data is consistent with expectations established in rock physics. Gas has a much lower bulk modulus than oil and water, resulting in a pronounced reduction in the saturated bulk modulus and the P-wave velocity. Water, which has the highest fluid bulk modulus among the tested scenarios, contributes most to the effective incompressibility. The resulting order of V_p , acoustic impedance, and AVO amplitude is therefore physically interpretable rather than merely a statistical pattern [18],[21].

The AVO stage is particularly important for subsequent inversion because it converts elastic contrasts into observables that contain angle-dependent information. The Aki-Richards approximation is suitable for the precritical angles used here and provides a computationally efficient representation of the reflection response [9]. More accurate approaches based on Zoeppritz can be used when the contrasts become large or when the analysis extends to critical angles [10]. The current formulation thus represents a practical compromise between physical accuracy and computational efficiency.

The results also support the use of multi-attribute inversion rather than relying on a single elastic parameter. Acoustic impedance is useful for lithological discrimination, while combinations of $\lambda\rho$, $\mu\rho$, V_p/V_s , and the intercept gradient provide complementary sensitivity to fluid conditions [2],[18]. Recent work on neural networks and ensemble-based seismic inversion further indicates that combining multiple attributes can improve the stability of predictions and provide uncertainty information [29],[30].

Several limitations must nevertheless be acknowledged. First, this study is primarily a physics-based synthetic forward modeling framework; the manuscript does not include a comprehensive validation of field data using independent blind wells. Second, the Gassmann formulation assumes conditions under which its low-frequency fluid substitution approximation is appropriate [20],[21]. Third, the illustrative seismic figures depict controlled synthetic responses and should not be interpreted as a substitute for calibrated field reservoirs. Fourth, the physics-guided network was not benchmarked against an unconstrained (purely data-

driven) baseline trained on the same data, and its predictions were not validated on blind wells withheld from training; both comparisons are left as directions for future work. Future work should therefore couple the proposed workflow with measured field well data (well logs and core data), quantify uncertainty through ensemble simulations, and compare the Aki–Richards operator with exact Zoeppritz modeling for the final target reservoir [10],[17],[29].

CONCLUSIONS

This study led to the formulation of a physics-guided poroelastic forward modeling workflow that establishes an integrated link between three-dimensional porosity variability, fluid substitution, elastic properties, and pre-stack synthetic seismic responses. The proposed framework combines porosity realizations obtained via sequential Gaussian simulation (SGS), physics-guided neural network prediction, constraints derived from the physics of poroelastic rocks, Gassmann fluid substitution, and seismic forward modeling based on the Aki-Richards approximation. It thus provides a physically interpretable modeling chain linking reservoir properties to angle-dependent seismic signatures.

Integrating the three-dimensional porosity results obtained from SGS with physics-guided neural network prediction is an effective mechanism for increasing the available spatial data for model training, while maintaining physically consistent relationships between porosity, elastic stiffness, and density. The introduction of physical constraints into the learning process thus helps limit physically inconsistent predictions and yields a more interpretable representation of the variability in reservoir properties.

Fluid substitution experiments reproduce the expected physical order among gas, oil, and water saturation conditions. Gas saturation produces the weakest compressional response as well as the strongest synthetic AVO signature, while oil exhibits an intermediate response. Water saturation provides the highest effective compressional modulus and produces the lowest reflection amplitude at short offsets. These trends demonstrate the sensitivity of the proposed forward model to variations in interstitial fluid properties.

The reported calibration correlations 0.912 for compressional wave velocity (V_p), 0.801 for shear wave velocity (V_s), and 0.890 for density, indicate good agreement between the modeled elastic properties and the measured V_p , V_s and density logs of the F3 wells described in Section “Experimental data and modelling configuration”. These results confirm the ability of the physics-based poroelastic modeling framework to reproduce the key elastic trends required for subsequent seismic analysis.

Furthermore, the synthetic reflection coefficients of approximately 0.18, 0.10, and 0.04 for gas, oil, and water, respectively, combined with the distinct intercept and gradient behaviors for the different fluid scenarios, demonstrate the potential of angle-dependent seismic attributes for fluid discrimination within the modeled domain. These results thus show that combining elastic attributes with AVO-sensitive responses can improve fluid discrimination compared to an interpretation based solely on (V_p) and (V_s).

Overall, the proposed workflow provides a physically interpretable basis for hybrid seismic inversion and the characterization of fluid-sensitive reservoirs. The integration of stochastic porosity modeling, physics-driven learning, fluid substitution, and pre-stack seismic forward modeling provides a coherent framework for linking the heterogeneity of reservoir properties to observable seismic responses. Future work should focus primarily on validation using field

seismic and logging data, uncertainty quantification, and a direct comparison between approximate reflectivity operators notably the Aki-Richards operator and exact formulations based on the Zoeppritz equations. These developments will enable a more rigorous assessment of the robustness and generalizability of the physics-driven framework proposed for the practical characterization of reservoirs.

NOMENCLATURE AND ABBREVIATIONS

Abbreviations

AVO	Amplitude variation with offset (angle)
NN	Neural network
P-P	Compressional-to-compressional (reflection)
SGS	Sequential Gaussian simulation

Latin symbols

A, B	AVO intercept and gradient (dimensionless)
C_{ijkl}	Fourth-order elastic stiffness tensor (GPa)
D_{sim}	Simulated pre-stack seismic trace
$G, G_{sat}, G_{dry}, G_{min}$	Shear modulus: general, saturated, dry frame, mineral (GPa)
I_p	Acoustic (P-wave) impedance, $\rho \cdot V_p$ ($\text{g}/\text{cm}^3 \cdot \text{km}/\text{s}$)
$K, K_{sat}, K_{dry}, K_{min}, K_{fl}$	Bulk modulus: general, saturated, dry frame, mineral, pore fluid (GPa)
$L_{Total}, L_{Data}, L_{Phys}$	Total, data and physics terms of the loss function
N, P	Number of training samples and number of predicted outputs
$N(t)$	Additive coherent noise
R_{PP}	P-P reflection coefficient
t	Two-way travel time (s)
u	Displacement field (m)
v, V_p, V_s	Wave velocity; compressional- and shear-wave velocities (km/s)
$w(\theta, t)$	Ricker source wavelet
$y, \hat{y}$	Calibration target and network prediction

Greek symbols

ε_{kl}	Strain tensor (dimensionless)
θ	Angle of incidence ($^\circ$)
λ	Physics-regularization weight in Eq. (4) (dimensionless)
$\lambda\rho, \mu\rho$	Lamé's first parameter and shear modulus multiplied by density ($\text{GPa} \cdot \text{g}/\text{cm}^3$)
$\rho, \rho_{sat}, \rho_{fl}, \rho_{min}$	Density: bulk, saturated, pore fluid, mineral (g/cm^3)
σ_{ij}	Stress tensor (GPa)
φ, φ_c	Porosity and critical porosity (fraction)

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