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REVIEW

Advances in theoretical and technical approaches for seismic prediction of reservoir permeability

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Abstract

Reservoir permeability serves as a critical parameter for unconventional reservoir characterization and hydrocarbon recovery optimization. However, complex petrophysical mechanisms and multifactorial coupling make its seismic prediction face significant challenges. This review comprehensively synthesized advances and limitations across three dominant methodologies: (i) dispersion/attenuation-based methods, limited by petrophysical assumptions, scaling issues, and non-uniqueness; (ii) pore structure-constrained methods, enhancing prediction accuracy but hindered by oversimplification and high-dimensional inversion instability; and (iii) artificial intelligence frameworks, offering data efficiency yet challenged by error propagation, overfitting vulnerability, and geologically implausible extrapolation. Comparative analysis revealed core bottlenecks in inadequate multiscale coupling between petrophysical mechanisms and data-driven approaches. These challenges are compounded by the absence of cross-disciplinary validation frameworks. To address these challenges, this review integrated interdisciplinary perspectives from seismic exploration, petrophysics, and machine learning. It proposed a tripartite permeability prediction paradigm unifying physical mechanisms, data-driven techniques, and engineering validation. This framework encompasses: first, advancing multi-porosity fluid-solid coupling theory and pore structure-constrained rock physics models; second, constructing physics-guided multimodal learning architectures that deeply embed differentiable physical laws (e.g., Darcy-Biot theory) within cross-scale physics-informed neural networks, coupling microscopic pore network simulations with macroscopic seismic responses; third, establishing a closed-loop workflow covering digital rock core simulations, blind well testing validation, production history matching, and dynamic data-driven evolution, thereby forming a quantifiable and iteratively upgradable technological system. This paradigm provides a multiscale approach for accurately characterizing permeability in unconventional reservoirs, and it establishes foundational theoretical principles and delineates practical implementation pathways for economically viable unconventional resource development.

Keywords: Geophysical exploration; Reservoir permeability; Dispersion and attenuation; Pore structure; Artificial intelligence

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1. Introduction

Reservoir permeability is a critical parameter for unconventional reservoir classification. It directly governs reservoir simulation outcomes and serves as an essential element in reservoir engineering, with significant implications for field development.[1-3] Seismic data provide a cost-effective characterization of lateral formation distribution and inter-well reservoir properties due to their extensive spatial coverage and relatively low acquisition costs. Therefore, to enhance prediction accuracy, developing effective seismic prediction methodologies for reservoir permeability holds substantial theoretical and practical value for optimizing the exploration and development of low-porosity and low-permeability reservoirs.[4]

Research on geophysical permeability prediction has primarily evolved along three trajectories over recent decades:[5] (i) numerical simulations grounded in classical rock physics models or laboratory core measurements, (ii) well-log-based permeability interpretation, and (iii) seismic inversion of permeability parameters. While core measurements deliver high accuracy, they are expensive, time-intensive, and spatially limited to discrete sample points. Well-log-based permeability offers continuous vertical profiles with moderate accuracy but remains costly and inherently localized ("single-well" perspective), lacking lateral continuity for areal development guidance. In contrast, seismic methods provide economically viable and laterally extensive formation characterization. Nevertheless, the complex and non-explicit relationship between permeability and seismic responses, compounded by multifactorial controls, renders seismic permeability prediction a persistently challenging frontier.

A pivotal 2001 United States Department of Energy workshop engaged 15 experts from industry, national labs, and academia to evaluate the detectability and invertibility of permeability within seismic data. Pride's synthesis confirmed that permeability information resides within seismic-frequency observations and outlined potential inversion frameworks, catalyzing significant research momentum.[6] Current seismic permeability prediction methodologies converge on three dominant approaches: dispersion/attenuation-based methods, pore structure-based techniques, and artificial intelligence (AI)-driven solutions.

Seismic permeability prediction currently resides in a phase of methodological exploration, challenged by the strongly nonlinear and implicitly coupled mechanisms between permeability and seismic responses. Permeability is governed by multifaceted controls, notably pore-throat architecture. These controls fundamentally impede the establishment of robust porosity and permeability mapping models based solely on core or well-log data. Consequently, effective permeability prediction in complex reservoirs remains elusive. Despite inherent obstacles, including theoretical model misfit and solution non-uniqueness, seismic permeability prediction persists as a frontier research focus. It lies at the interface of geophysics and reservoir engineering. This persistence is driven by its critical value in dynamic reservoir characterization. Recent advances in deep learning have accelerated data-driven methodologies. However, three persistent bottlenecks endure: (i) traditional rock physics models, such as the Biot-Squirt (BISQ) framework, exhibit limited generalizability in highly heterogeneous formations, failing to accurately quantify the coupling of pore-throat architecture with seismic wavefields; (ii) machine learning approaches establish nonlinear mappings, but they suffer from interpretability deficits and physical decoupling, producing predictions unconstrained by geological plausibility; and (iii) multiscale data integration across core-log-seismic domains lacks standardized protocols, with information degradation during upscaling constraining prediction accuracy.

This review systematically synthesized technological advancements in seismic permeability prediction through a structured analysis of three dominant methodologies: dispersion/attenuation-based techniques leveraging frequency-dependent velocity characteristics, pore structure-oriented approaches, and AI-driven solutions employing deep learning architectures. By evaluating the theoretical foundations, technical advantages, and limitations of these paradigms, we proposed a transformative "dual-engine" predictive framework that embedded rock physics constraints within deep learning infrastructures. This mechanism and data co-driven model integrates theoretical rigor with data-adaptive capability, particularly through physics-informed neural networks. As a result, the model overcomes applicability barriers in complex reservoirs where traditional methods falter.

The subsequent sections of this paper are organized as follows: Section 2 elaborates on the theoretical foundations and representative techniques of dispersion/attenuation-based methods. Section 3 focuses on the key technologies and applications of pore structure-based methods. Section 4 analyzes the progress and challenges of AI-driven solutions. Section 5 explores potential future research directions. Finally, Section 6 concludes the review.

2. Permeability prediction methods based on dispersion and attenuation

These approaches comprise three primary categories: (i) theoretical model-based inversion, (ii) velocity dispersion/quality factor prediction, and (iii) fluid mobility attribute prediction.

2.1. Model-based inversion

Theoretical forward modeling investigates how reservoir parameters (e.g., porosity, permeability, and fluid saturation) influence seismic wave propagation characteristics (e.g., dispersion, attenuation, and reflection coefficients), providing foundations for geophysical parameter inversion. Typically, this inversion seeks an optimal permeability value within predefined bounds, minimizing misfit between model-predicted and observed P-wave velocity dispersion or quality factor, effectively transforming permeability estimation into an optimization problem. Some typical model-based inversion methods are summarized in Table 1.

The BISQ model, incorporating both Biot flow and squirt flow mechanisms, effectively explains high dispersion/attenuation in seismic frequencies. Nie *et al.*[7] implemented BISQ-based inversion using niche genetic algorithms, while Zhang *et al.*[8] derived 3D anisotropic dispersion equations and analyzed azimuthal dispersion effects on permeability inversion. To address inherent limitations of genetic algorithms (e.g., premature convergence and poor local search), Fang and Yang[9] developed a hybrid genetic-simulated annealing algorithm demonstrating superior accuracy and convergence. In addition, a series of advancements in reservoir parameter inversion was achieved based on the BISQ model.[10,11] White[12] and White *et al.*[13] complemented the macroscopic-scale Biot theory and microscopic-scale squirt flow mechanisms and introduced a mesoscopic dissipation mechanism, finally deriving frequency-dependent attenuation and dispersion functions for partially saturated porous media parameterized using permeability, porosity, and pore-fluid properties. Johnson[14] subsequently extended White's model to accommodate arbitrarily sized fluid patches by incorporating geometric characteristic parameters S/V and T. Later, Sun[15] integrated these tri-scale (macro-meso-micro) dispersion-attenuation mechanisms to develop the Biot-patchy-squirt (BIPS) model, which characterized wave dispersion and attenuation in immiscible fluid-saturated fractured poroelastic media. In the aforementioned models, permeability characterization requires inversion through attenuation response without establishing an explicit theoretical relationship. For example, in the mesoscopic White's layered patchy saturation model, White[12] derived the expression for the complex modulus of P-waves ($E[\omega]$), which implicitly encoded permeability information. Relying on this discovery and applying plane wave theory, one can compute the phase velocity (V_p) and inverse quality factor (Q^{-1}).

$$E(\omega)=\left\{\frac{1}{K_{\mathrm{BGH}}+(4/3)N}+\frac{2(\gamma_2-\gamma_1)^2\sqrt{\dfrac{\kappa}{\eta}}}{\sqrt{i\omega}(L_1+L_2)\cdot\displaystyle\sum_{j=1}^{2}\sqrt{K_{E_j}}\coth\left(\frac{L_j}{2}\sqrt{\frac{i\omega}{\frac{\kappa}{\eta}K_{E_j}}}\right)}\right\}^{-1} \quad \text{(I)}$$

$$V_{\mathrm{p}}=\left(\mathrm{Re}\left(\sqrt{\frac{(1-\phi)\rho_{\mathrm{s}}+\phi(S_1\rho_{\mathrm{f}_1}+S_2\rho_{\mathrm{f}_2})}{E(\omega)}}\right)\right)^{-1} \quad \text{(II)}$$

$$Q^{-1}=\frac{\mathrm{Im}\left(\dfrac{E(\omega)}{(1-\phi)\rho_{\mathrm{s}}+\phi(S_1\rho_{\mathrm{f}_1}+S_2\rho_{\mathrm{f}_2})}\right)}{\mathrm{Re}\left(\dfrac{E(\omega)}{(1-\phi)\rho_{\mathrm{s}}+\phi(S_1\rho_{\mathrm{f}_1}+S_2\rho_{\mathrm{f}_2})}\right)} \quad \text{(III)}$$

where L denotes the thickness of the porous layer, K_{BGH} represents Hill's approximate expression of the Gassmann modulus at high frequencies, N signifies the shear modulus of the dry rock frame, γ indicates the ratio of fast P-wave fluid tension to total stress, η refers to the viscosity coefficient, κ designates the permeability, ω is the angular frequency, K_E denotes the effective modulus of

Table 1. Theoretical and application characteristics of typical model-based inversion methods

Model name	Core mechanism	Target reservoir type	Permeability representation
BISQ	Coupling of Biot flow and squirt flow	Medium-high porosity/permeability sandstones	Implicit (inverted via attenuation response)
White/Johnson	Mesoscopic fluid patch dissipation	Partially saturated porous media	Implicit (inverted via attenuation response)
BIPS	Macro-meso-micro coupling	Fracture-pore dual media	Implicit (inverted via attenuation response)
Geometric network model	Parametrization of elliptical pore/fracture geometry	Fracture-pore/fracture reservoirs	Explicit equation

Abbreviations: BIPS: Biot-patchy-squirt; BISQ: Biot-Squirt.

compressional wave, S represents the fluid saturation, and ρ_S and ρ_f are the densities of the grain mineral and pore fluid, respectively.

The following equations provide a methodology for establishing explicit permeability representation relationships. For example, Xiong *et al.*[16] and Wei *et al.*[17] established a 3D network model with elliptical cross-sections for fractures and soft pores. They incorporated permeability relationships with porosity, confining pressure, and pore aspect ratio, deriving a computational methodology for permeability estimation.

$$\kappa(\omega) = \frac{\eta L}{A} \cdot \frac{(\chi \cdot P_U + \delta \cdot P_D)}{P_U - P_D} \tag{IV}$$

$$\chi = 2\left(\frac{\alpha^3}{1+\alpha^2}\right)\frac{-\mathrm{i}\pi R^2}{\rho_f c}\left(\frac{\cos(\omega L/c)}{\sin(\omega L/c)}\right)\left(\frac{2J_1(KR)}{KRJ_0(KR)} - 1\right) \tag{V}$$

$$\delta = 2\left(\frac{\alpha^3}{1+\alpha^2}\right)\frac{\mathrm{i}\pi R^2}{\rho_f c}\left(\frac{1}{\sin(\omega L/c)}\right)\left(\frac{2J_1(KR)}{KRJ_0(KR)} - 1\right) \tag{VI}$$

where η denotes the fluid viscosity, L represents the length of the microtube, A indicates the cross-sectional area ($\alpha\pi R^2$), R is the semi-major axis radius of the elliptical cross-section, α refers to the aspect ratio of the fracture cross-section, P_U and P_D denote the pressure at both ends of the microtube, respectively, ρ_f signifies the density of the fluid within the microtube, J designates the zeroth-order Bessel function of the first kind, K represents $K = \sqrt{\frac{\mathrm{i}\omega\rho_f}{\eta}}$, and C is the acoustic wave velocity in the fluid.

Tan *et al.*[18] integrated the coupled effects of solid particle detachment, fluid-solid coupling, multiphase flow, and stress sensitivity into a fluid and structure-coupled stress-sensitive permeability model grounded in material mechanics and fractal theory. They thus provided theoretical guidance for accurate prediction of flow behavior and development optimization in stress-sensitive reservoirs.

It is evident that most existing pore media and fracture-pore media models implicitly incorporate permeability information. However, they fail to establish explicit theoretical permeability relationships. Alternatively, the developed permeability models contain numerous physical parameters of the rock matrix. These parameters hinder direct permeability prediction using exploration data. Furthermore, the inversion process reveals that the effectiveness of rock physics inversion critically depends on the accuracy of elastic parameters derived from prestack seismic data and the congruence between rock physics models and actual formation properties. Key limitations of model-based permeability inversion include: (i) solution non-uniqueness and low noise tolerance, (ii) significant result divergence across different dispersion-attenuation models despite generally consistent permeability response patterns in forward modeling, and (iii) frequent mismatches between theoretical predictions and field observations.

2.2. Velocity dispersion/quality factor-based methods

In field applications, acquiring comprehensive velocity dispersion data at every sampling point remains challenging. Theoretical forward modeling generally indicates an inverse relationship between permeability and dispersion: low permeability correlates with high dispersion, while high permeability corresponds to low dispersion.

Following this principle, Liu[19] applied frequency-dependent amplitude variation with offset (AVO) theory to quantify P-wave velocity dispersion as a fluid mobility proxy for permeability prediction. Yuan *et al.*[5] established permeability and dispersion relationships through core-derived rock physics analysis and determined the first-order relative variation of Young's modulus with seismic frequency and the second-order relative variation of permeability with pressure. Then, subsequent frequency-dependent amplitude variation with incident angle (AVA) inversion of well logs yielded the reservoir's P-wave dispersion, enabling permeability prediction through the derived relationships. Wu *et al.*[20] developed a quality factor-based method, which involved correlation between averaged core permeability and well quality factors, and then they estimated permeability at unlogged locations through seismic waveform similarity analysis to reference wells.

The intrinsic limitations of dispersion attribute methods originate from fundamental physical and operational constraints:[21,22] conventional seismic bandwidth (10–100 Hz) fails to excite significant dispersion effects in high-permeability reservoirs (κ >10 mD). This failure occurs due to fluid pressure diffusion thresholds below 10 Hz, which critically attenuate permeability sensitivity. This bandwidth confinement triggers a cascading degradation: high-fidelity Q-factor inversion demands ultrabroadband data (>3 octaves), yet narrow field-acquisition bandwidths (<2 octaves) propagate

Q-estimation errors into permeability predictions. Further compounded by anisotropic scattering, fracture azimuthal variability induces phase velocity dispersion anomalies that mask permeability signatures. Collectively, these interdependencies form an error amplification chain. The chain restricts dispersion-based methods to homogeneous siliciclastic reservoirs with moderate permeability, while faltering in fractured or stress-sensitive formations. Collectively, these constraints necessitate addressing two persistent bottlenecks: (i) non-unique solutions in frequency-dependent AVO/AVA dispersion attribute inversion and (ii) significant relative errors in current Q-factor extraction techniques, compromising permeability estimation accuracy.

2.3. Fluid mobility-based methods

Fluid mobility (M), defined as the ratio of reservoir permeability (κ) to fluid viscosity (η), characterizes the coupled effects of pore structure's conductivity and pore fluid viscosity. At present, fluid mobility-based methods constitute the predominant approach for permeability prediction within dispersion-attenuation frameworks.

In 2004, Silin *et al.*[23] derived the low-frequency asymptotic reflection coefficient for fluid-saturated porous media:

$$R = \frac{Z_1 - Z_2}{Z_1 + Z_2} + R_1 \frac{1+i}{\sqrt{2}} \sqrt{\left| \mathrm{i}\left(\frac{\kappa}{\eta} \rho_f \omega \right) \right|} + \cdots \quad \text{(VII)}$$

where Z denotes impedance, ρ_f is fluid density, and ω is angular frequency. This equation establishes a positive correlation between the reflection coefficient and the square root of the product term. Goloshubin *et al.*[24] and Goloshubin *et al.*[25] subsequently proposed a novel frequency-dependent imaging attribute when analyzing dual-porosity media attenuation. Proportional to $\sqrt{M}$, this attribute was applied to reservoir permeability estimation. On this basis, Chen *et al.*[26] developed a computational expression for fluid mobility attributes and established a method to identify the dominant frequency within the low-frequency band of seismic signals. This approach enabled the direct calculation of reservoir fluid mobility using the instantaneous spectrum of the low-frequency dominant frequency. The computational expression is given as follows:

$$M \approx \frac{1}{C^2} \left[\frac{dA(\omega)}{d\omega} \right]^2 \omega \quad \text{(VIII)}$$

where C is a proportionality coefficient, ω is the dominant low frequency, and $A(\omega)$ is the amplitude spectrum of the low-frequency band derived from time-frequency analysis.

This framework facilitates subsequent methodological advances. For example, Zhao *et al.*[27] investigated the effects of fluid mobility on dispersion and attenuation using dual-porosity and dual-permeability models. Lu[28] developed a Bayesian framework for direct mobility inversion. Zhang *et al.*[29] enhanced reservoir prediction accuracy by integrating the synchro-squeezed generalized S-transform with Lucy-Richardson deconvolution into mobility computation.

The model-based inversion approach in Section 2.1 and the permeability prediction technique using dispersion/attenuation attributes in Section 2.2 were compared. The comparison revealed that the core advantage of the latter method lies in circumventing Q-factor extraction errors and directly establishing a quantitative correlation between seismic amplitude and fluid mobility. Application to actual marine seismic data from the JZ area of the Bohai Sea demonstrated that the fluid mobility attribute exhibits significant imaging advantages for hydrocarbon reservoirs. It enables precise spatial delineation of reservoir distribution while substantially reducing the non-uniqueness and uncertainty in fluid identification. A representative case study from Chen *et al.*[26] illustrated these capabilities (Figure 1). The fluid mobility measurement profile displays a high-amplitude "bright spot" anomaly at the gas reservoir location, while the fluid mobility slice extracted along the gas-bearing interval clearly delineates the spatial boundaries of high-permeability zones (outlined by black dashed contours).

Most current methods approximate mobility attributes through time-frequency decomposition for qualitative permeability assessment. However, reservoir thickness below λ/8 induces significant low-frequency amplitude distortion, which requires integrated compensation through high-frequency tuning effects, combined with subjectivity in dominant frequency selection and the petrophysical-property dependency of calibration coefficient C. Consequently, these thin-bed resolution constraints collectively result in fundamental limitations of such methods: Uncertainties artificially introduced by the subjective determination of ω, potentially misrepresenting true reservoir mobility; and the inherently limited resolution of mobility attributes derived from time-frequency decomposition methods.

2.4. Challenges of dispersion/attenuation-based methods

The model categories, theoretical bases, applicable conditions, advantages, and limitations of various dispersion/attenuation-based permeability prediction approaches are systematically compared in Table 2. This comparison reveals that despite the clear physical mechanisms underpinning this category of methods, four fundamental challenges persist: (i) controversies regarding the universality of petrophysical assumptions, such as deviations between assumed pore-scale homogeneity and actual reservoir heterogeneity, (ii) scale adaptability conflicts due to mismatched micro-mechanisms and macro-scale seismic observations, (iii) bandwidth limitations of seismic data, where the absent of low-frequency components induce significant fluid mobility estimation bias, and (iv) amplified solution non-uniqueness due to coupled controls of pore geometry, fluid viscosity, and fracture density on dispersion/attenuation responses.

3. Permeability prediction based on pore structure characteristics

Traditional seismic permeability prediction methods primarily rely on well-log or laboratory rock physics data. These methods establish optimal porosity and permeability relationships and then extrapolate these petrophysical correlations to seismic data for areal

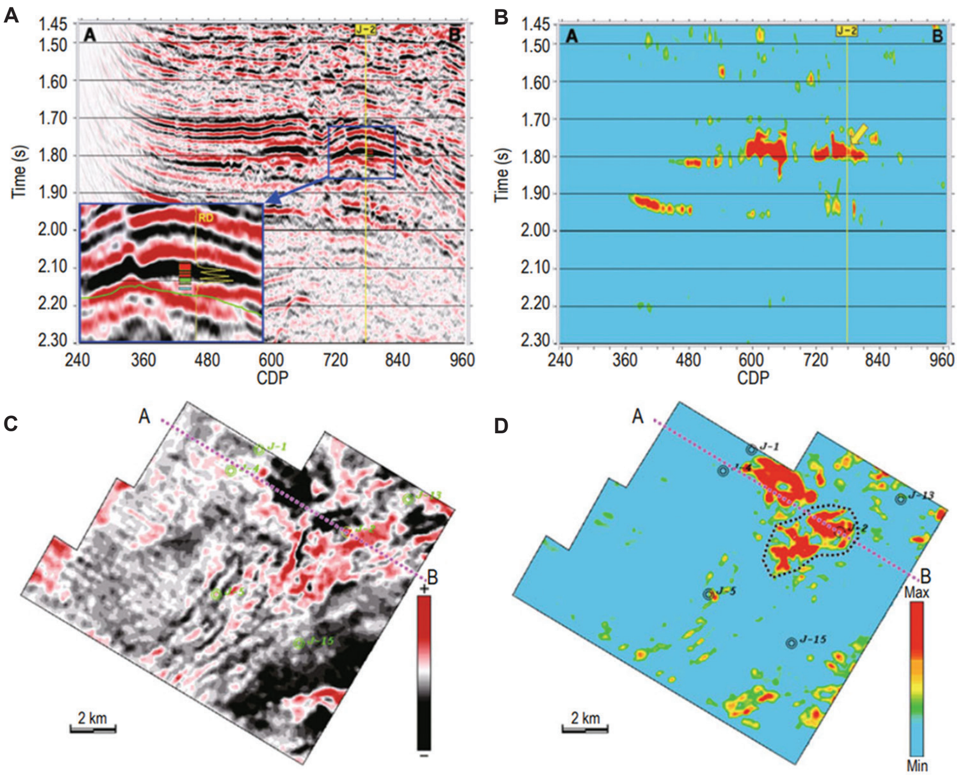

Figure 1. Fluid mobility analysis of reservoirs in the lower Ed2 formation from the JZ area. (A) Seismic section. (B) Fluid mobility reservoir section. (C) Seismic slice. (D) Fluid mobility reservoir slice. The colors red, green, and blue in the well log in the zoomed image indicate gas, oil, and brine, respectively. Reprinted with permission from Chen *et al.*[26] Copyright 2012 Editorial Office of Applied Geophysics and Springer-Verlag Berlin Heidelberg. Abbreviation: CDP: Common depth point.

Table 2. Theoretical and application characteristics of dispersion/attenuation-based methods

Model category	Theoretical basis	Applicable conditions	Advantages	Limitations
Model-based inversion	BISQ/BIPS theoretical models	Moderate-to-high porosity/permeability sandstones	Clear physical interpretation	Mismatch in strongly heterogeneous reservoirs
Velocity dispersion/quality factor-based methods	Velocity-frequency response	Broadband seismic data	High computational efficiency	Sensitive to Q-factor extraction errors
Fluid mobility-based methods	Low-frequency reflectivity theory	Fluid-saturated porous media	Direct indicator of flow capacity	Resolution constraints in time-frequency analysis

Abbreviations: BIPS: Biot-patchy-squirt; BISQ: Biot-Squirt.

permeability prediction.[30] However, due to depositional and diagenetic controls, carbonate reservoirs, particularly reef-shoal facies, exhibit significantly more complex pore architecture than clastic reservoirs. These reservoirs demonstrate substantial permeability heterogeneity even at comparable porosity levels. In lithofacies-varying formations with intricate pore systems, conventional methods yield compromised accuracy due to nonlinear porosity and permeability relationships. Consequently, pore structure integration becomes essential for reducing inversion non-uniqueness and enhancing prediction reliability.

There are currently three pore structure-based approaches: (i) Sun model-based inversion, (ii) lithofacies-constrained prediction using pore-structure parameters, and (iii) dual-porosity structure parameter integration.

3.1. Sun model-based methods

Sun[31,32] derived two pore structure parameters through fundamental rock physics analysis: the bulk compliance factor (γ), which characterizes volumetric rock deformation, and the shear compliance factor (γ_μ), which describes shape variations. Both γ and γ_μ satisfy the rock physics relationship:

$$K_d = K_m (1\text{-}\phi)^{\gamma} \tag{IX}$$

$$\mu_d = \mu_m (1-\phi)^{\gamma_\mu} \tag{X}$$

where K_d and μ_d denote the bulk modulus and shear modulus of dry rock, respectively; K_m and μ_m represent the bulk modulus and shear modulus of the grain mineral phase, respectively; and ϕ signifies porosity. Furthermore, γ_μ can be expressed as:

$$\gamma_\mu = \frac{\lg(V_s^2 \rho) - \lg \mu_m}{\lg(1-\phi)} \tag{XI}$$

where V_s, ρ, and ϕ denote the S-wave velocity, density, and porosity, respectively.

Applied to Texas carbonate reservoirs by Dou *et al.*,[33] these parameters effectively characterized the relationship between porosity impedance and permeability. They facilitated the identification of pore types and high-permeability zones, thereby enhancing prediction accuracy. Zhang *et al.*[34] subsequently implemented these parameters in the Puguang Gas Field, with a pore structure-constrained porosity and permeability binary model developed for permeability-type classification at seismic scales. Similarly, Jin *et al.*[35] established pore-type discrimination criteria and type-specific porosity and permeability models using γ_μ. These achievements enabled refined well-log permeability interpretation. By analyzing elastic parameter-pore structure relationships across pore types, rock physics templates for the permeability prediction of complex reservoirs were constructed (Figure 2). In the case study of Puguang Gas Field (Figure 3), an intraparticle pore-dominated reservoir within the 5369–5440 m interval was developed in Well PG302-1. Although this section exhibited relatively high predicted porosity, the pore structure parameter was significantly low, indicating low permeability consistent with core analysis results. This case validates that permeability prediction based on pore structure parameters effectively discriminates reservoir flow capacity heterogeneity, thereby delineating the spatial distribution of high-permeability zones. Compared to conventional approaches, this method substantially enhances permeability prediction accuracy in complex reservoirs. Conventional methods rely on statistically derived empirical formulas for porosity and permeability, with prediction errors often exceeding one order of magnitude. Critically, these findings substantiate that pore structure exerts dominant control over permeability, whereas porosity serves merely as a contributory factor.

The Sun model demonstrates porosity-independent permeability prediction capabilities in both carbonate and clastic reservoirs. It achieves this through its characterization of rock deformation mechanisms through γ and γ_μ. However, the model suffers from fundamental flaws in its physical foundation. First, the model exclusively captures elastic deformation responses while neglecting the topological control mechanisms governing fluid pathways (e.g., pore-throat connectivity). Second, its classification regression framework contains inherent structural deficiencies: oversimplified permeability zoning based solely on γ or γ_μ results in ambiguous partition boundaries, and the enforcement of linear porosity and permeability regressions contradicts the intrinsic nonlinearity of

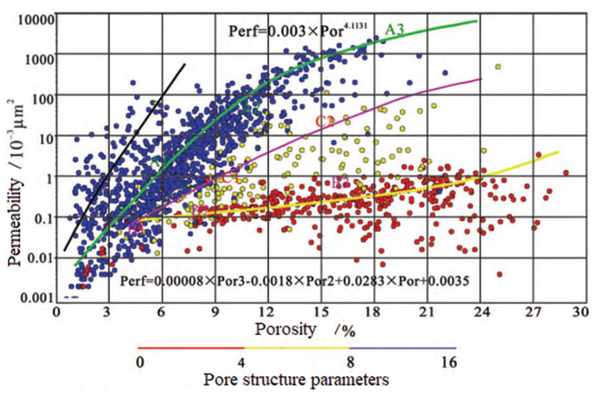

Figure 2. Permeability interpretation chart of Puguang Gas Field. Reprinted with permission from Jin *et al.*[35] Copyright 2016 Journal of Palaeogeography.

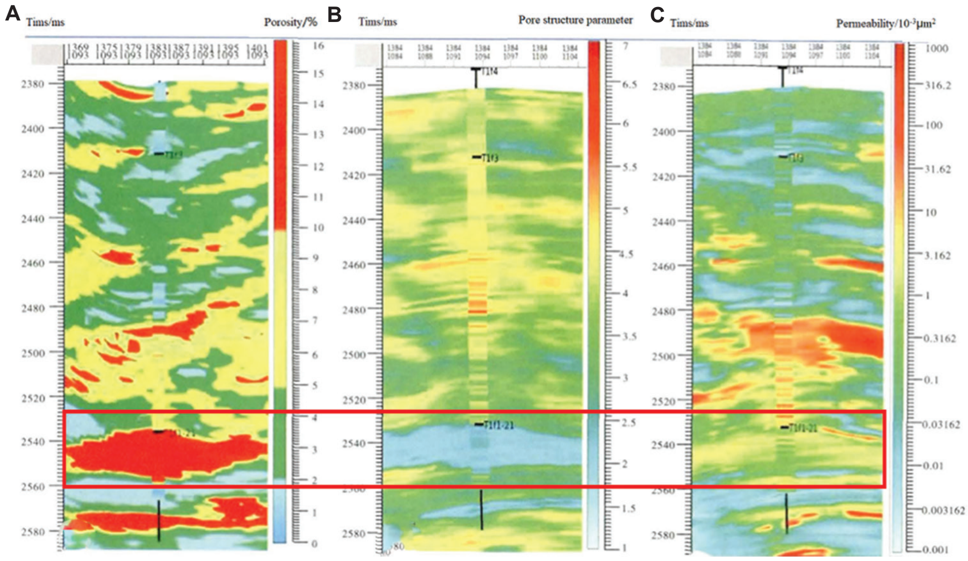

Figure 3. Inversion profiles of (A) predicted porosity, (B) pore structure parameter, and (C) permeability through Well PG302-1. Reprinted with permission from Jin *et al.*[35] Copyright 2016 Journal of Palaeogeography.

carbonate systems, particularly the exponential porosity–permeability relationships observed in vugular pore networks.

3.2. Lithofacies-controlled methods with pore structure parameters

Advancing quantitative reservoir characterization recognizes depositional microfacies as primary controls on petrophysical properties. Sedimentary attributes, including composition and grain size, fundamentally govern porosity and permeability distributions. Therefore, establishing microfacies-constrained property models is essential.

Zhao[36] derived facies-control factors from Archie's equation, integrating them with permeability through Kozeny's hydrodynamic formula to develop a facies-constrained permeability calculation method for seismic inversion. This approach demonstrably enhances lateral prediction accuracy by incorporating geological priors. Given the primary control of pore structure on permeability as introduced in Section 3.1, Gan *et al.*[37] developed a comprehensive workflow for reservoir permeability prediction integrating pore structure and lithofacies controls: First, lithofacies classification was conducted using the reservoir zone's porosity, elastic parameters, and γ_μ. Then, facies-specific multivariate regression was used for permeability prediction. Relying on this workflow, they selected the Fudong Slope area in the eastern central depression belt of the Junggar Basin as the study area for method application. The primary reservoir type in this region is lithologic-stratigraphic hydrocarbon accumulation. The study designated Well FUD7 as the training well and Well FUD6 as the prediction well. Regression relationships were separately established for different lithofacies in the training well. Subsequently, the trained lithofacies-specific regression models were applied to the prediction well to obtain permeability prediction results. Comparative analysis with non-facies-based multivariate regression in Table 3 reveals that both wells exhibited reduced prediction errors and enhanced coefficient of determination (R^2) values after facies-control implementation. The maximum error reduction and greatest R^2 improvement occurred when γ_μ was included in the regression parameters. Field applications demonstrate that this method can confine permeability prediction errors within one order of magnitude, and multivariate regression proves to be a viable solution for reservoir permeability prediction as it incorporates elastic parameters and γ_μ under lithofacies constraints.

While lithofacies-controlled methods enhance prediction accuracy through depositional microfacies constraints, precise lithofacies classification remains a prerequisite for permeability prediction, as it serves as a geological prior. Furthermore, γ_μ exhibits extreme sensitivity to velocity and density errors in seismic inversion. Acting as a key input for lithofacies classification, it forms a positive error feedback loop propagating through the workflow. Strong multicollinearity also exists among porosity, γ_μ, and impedance in multivariate regression. This multicollinearity distorts the physical significance of the regression coefficients, and these factors collectively cause abrupt lateral prediction jumps exceeding one order

Table 3. Statistics of mean square error (MSE) and coefficient of determination (R^2) for multivariate regressions

Key input parameters	Facies-based	Fud7 well		Fud6 well	
		MSE	R^2	MSE	R^2
ϕ	No	0.9599	0.4392	1.5056	0.3269
	Yes	0.9387	0.5067	1.2961	0.5250
$\phi+Vp$	No	0.9569	0.4409	1.4026	0.3508
$\phi+Vp/Vs$	No	0.9239	0.4602	1.4014	0.3921
$\phi+\gamma_\mu$	No	0.7765	0.5463	1.3564	0.4961
$\phi+Vp+Vp/Vs$	No	0.8975	0.4757	1.0756	0.4989
	Yes	0.8924	0.5408	0.9542	0.5925
$\phi+Vp+Vp/Vs+\gamma_\mu$	No	0.7421	0.5664	0.9356	0.6016
	Yes	0.6721	0.7948	0.8943	0.7924

γ_μ indicates shear compliance factor; ϕ indicates porosity; V_P indicates P-wave velocity; V_s indicates S-wave velocity.

of magnitude. In summary, the limitations of this method include: High sensitivity to seismic lithofacies and pore structure parameters that are intrinsically challenging to quantify accurately; prevalent multicollinearity in multivariate regression; and multiple pore structure factors must be incorporated, given the multivariate nature of permeability controls.

3.3. Dual-pore-structure parameters methods

Wei and Innanen[38] discovered the combined effects of pore morphology and scale on permeability, establishing a dual-parameter model:

$$\kappa = A\phi^B\left(\frac{\phi}{C}\right)^{0.5-\gamma_p} \tag{XII}$$

where

$$\gamma_p = W_p\gamma_s + (1-W_p)(1-\gamma_c) \tag{XIII}$$

where κ represents permeability; γ_s and γ_c denote scale and roundness parameters, respectively; W_p is a weighting coefficient determined from the core and log data; and A, B, and C are undetermined coefficients. Inspired by the Sun model in Section 3.1, and guided by the lithofacies-control rationale established in Section 3.2, Ding *et al.*[39] derived a shear-Lee factor (c_μ) from the Lee model. This factor exhibited a strong linear correlation with principal pore dimensions. By incorporating this factor, they effectively integrated both pore-scale and morphological effects. In addition, they integrated the factor with elastic parameters, porosity, and pore aspect ratios (α) as inputs for a feedforward neural network to predict lithofacies, and then subsequently predicted permeability, ultimately constraining prediction errors within half an order of magnitude. Field application (Figure 4) in the tight gas reservoirs of the Shaximiao Formation, Jinqiu Gas Field, Sichuan Basin, demonstrated that predictions incorporating dual-pore-structure parameters (c_μ+α) achieved superior outcomes compared to single-factor (γ_μ) approaches. These predictions quantitatively matched well-logs with higher fidelity and generated sand bodies with enhanced spatial continuity.

The dual-pore-structure parameter approach demonstrates progress in characterizing the combined effects of pore morphology and scale on permeability. However, it suffers from inherent limitations in its physical mechanisms. The model oversimplifies complex flow processes into a power law combination of morphology and scale, neglecting the fundamental control of pore topology connectivity (e.g., tortuosity of pore throats). More critically, the parameterization exhibits irresolvable ambiguity: the model fails to distinguish the opposite effects on permeability between the real-scale expansion of pore throats and the morphological distortion caused by the flattening of sheet-like pores. In industrial applications, high-dimensional inversion spaces introduce significant uncertainties: the Wei model requires simultaneous resolution of multiple interacting parameters. Its high-dimensional solution space causes pronounced oscillation in inversion results. Meanwhile, Ding's neural network framework faces triple error propagation: inherent errors in elastic parameters derived from seismic inversion directly propagate into the calculation of the shear-Lee factor. This propagation induces intermediate parameter bias. Subsequent coupling of multi-source inputs in hidden layers of the feedforward network further iteratively amplifies upstream errors through weight matrices, ultimately generating substantial errors in the output layer's permeability predictions.

3.4. Challenges of pore structure characteristics-based methods

Although existing mainstream porosity and permeability prediction models (e.g., Sun, Wei, and Ding models) demonstrate progress in specific scenarios or mathematical formulations, they still suffer from fundamental limitations, as summarized in Table 4 regarding their methodologies, advantages, and constraints. These limitations include their core physical mechanisms, such as the neglect of pore-throat connectivity control and the ill-defined physical interpretations of parameters; model architecture, such as arbitrarily imposed linearization and error-amplifying designs; and application feasibility, such as dependence

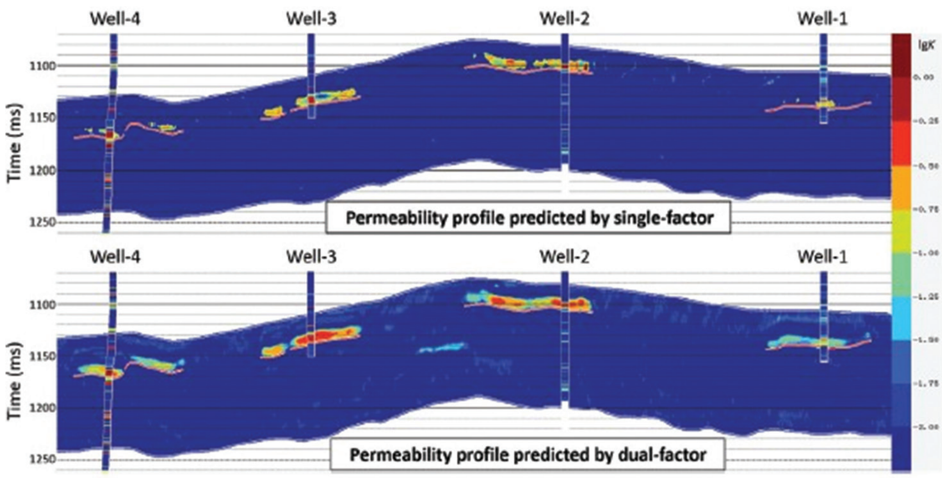

Figure 4. Predicted permeability profiles, where dual-pore-structure parameters refer to $c_\mu+\alpha$ and single-factor denotes γ_μ. Reprinted with permission from Ding *et al.*[39] Copyright 2023 Society of Exploration Geophysicists.

Table 4. Theoretical and application characteristics of pore structure characteristics-based methods

Dimension	Sun model	Lithofacies-controlled model	Dual-parameter model
Principle	Rock physics	Sedimentology	Morphology+scale
Key input parameters	Bulk compliance factor and shear compliance factor	Lithofacies type, pore structure parameters	Scale parameter, roundness parameter
Parameter acquisition	Seismic/log elastic parameter inversion	Core calibration+seismic lithofacies division	Core calibration+seismic/log elastic parameter inversion
Lithofacies dependent	No	Yes	Optional
Advantages	Porosity-independent heterogeneity characterization	Geological prior integration reduces non-uniqueness	Morphology+scale
Limitations	Oversimplified classification ignores multi-factor coupling	Subjectivity in lithofacies delineation	High-dimensional parameter instability, dependent on upstream parameter accuracy
Reservoir applicability	Carbonate/clastic reservoirs	Highly heterogeneous carbonates/clastic reservoirs	Fracture-porosity systems
Prediction accuracy	Error≤1 order of magnitude	Error≤1 order of magnitude	Error≤0.5 order of magnitude
Reference	Jin *et al.*[35]	Gan *et al.*[37]	Ding *et al.*[39]

on difficult-to-acquire/high-error parameters and high-dimensional inversion instability with non-unique solutions.

4. Permeability prediction based on AI

In recent years, AI algorithms have emerged as powerful computational tools for solving complex non-linear mapping and high-dimensional data fitting problems. They trigger transformative advances across scientific and engineering domains. Within petroleum exploration, the inherent subsurface complexity and uncertainty present significant challenges. These challenges, combined with substantial human capital demands for analyzing massive exploration datasets, have accelerated the industry-wide integration of AI technologies.[40-43]

4.1. Data-driven AI approaches

The earliest Chinese research on seismic-driven permeability prediction traces back to a groundbreaking study published in Oil Geophysical Prospecting by Chen and Guo.[30] Grounded in the elastic wave theory of dual-phase media, the authors established the theoretical basis for permeability prediction from seismic data. They demonstrated that conventional approaches relying solely on porosity and permeability functional relationships could only delineate qualitative permeability trends. To enable quantitative prediction, they pioneered the integration of mathematical approximation techniques with seismic attributes. As seismic attribute and permeability relationships defy explicit mathematical formulation, AI serves as an advanced regression tool that correlates well-log permeability with adjacent seismic traces. This calibrated relationship can then be extrapolated across 3D seismic volumes for reservoir permeability prediction.

Based on Chen's work, He *et al.*[43] implemented the rough set theory for optimal attribute selection, followed by genetic algorithm-optimized backpropagation neural networks to establish attribute and permeability mappings. Anifowose *et al.*[44] conducted a comparative analysis of multiple algorithms for permeability estimation in Middle Eastern carbonates. The study used integrated seismic attributes and wireline logs. The algorithms evaluated include artificial neural networks, fast Newman algorithm, support vector machines, and extreme learning machines. Meanwhile, Zhen *et al.*[45] integrated a convolutional block attention module into a convolutional neural network to characterize sand-body development patterns and identify concealed channels.

Riyadi *et al.*[46] proposed a permeability estimation method utilizing elastic attributes derived from simultaneous seismic inversion and evaluated the predictive performance of several ensemble-based models, including extreme gradient boosting (XGBoost), light gradient boosting (LightGBM), categorical gradient boosting, bagging regressor, random forest, and stacking. A multilayer perceptron neural network algorithm was also assessed. They focused on the X Field in the Malay Basin, characterized by complex pore systems (coexisting intergranular pores, dissolution vugs, and fractures) and pronounced heterogeneity. The statistical evaluation of permeability prediction models was based on wireline logging data using the R^2 and root mean squared log error (RMSE). The results revealed that integrating porosity with elastic properties as combined input features yielded $R^2 > 0.95$ and root mean squared log error (RMSLE) < 0.174. Among the tested algorithms, LightGBM and stacking ensemble models delivered optimal performance ($R^2 = 0.97$, RMSLE = 0.112 for both), while random forest exhibited relatively inferior results (R^2 = 0.92, RMSLE = 0.174). In contrast, predictions using elastic properties alone demonstrated significantly reduced accuracy, with R^2 ranging from 0.82 to 0.87, and RMSLE from 0.195 to 0.278. Within this feature configuration, XGBoost achieved the highest precision (R^2 = 0.87, RMSLE = 0.195), closely followed by a multilayer perceptron with 16 hidden layers (R^2 = 0.87, RMSLE = 0.207). Figure 5 compares predicted and measured permeability from the best-performing models under both input scenarios. The contrast between the bottom panels in Figure 5 visually confirms substantial prediction challenges in low-permeability intervals (<0.001 mD) when exclusively using elastic properties. Collectively, these results demonstrate that feature selection and combination exert decisive influence on predictive efficacy even with high-performance models. This limitation arises because pore-throat dimensions, morphology, and connectivity—all critical controls on flow behavior—exert more dominant control in tight formations. In contrast, elastic properties have been proven insufficient to characterize such microstructural determinants of fluid transport.

Although purely data-driven AI models (black-box models) in the aforementioned studies enhanced the prediction accuracy of reservoir permeability, their fundamental flaw lies in intrinsic decoupling from the physical mechanisms governing fluid flow.

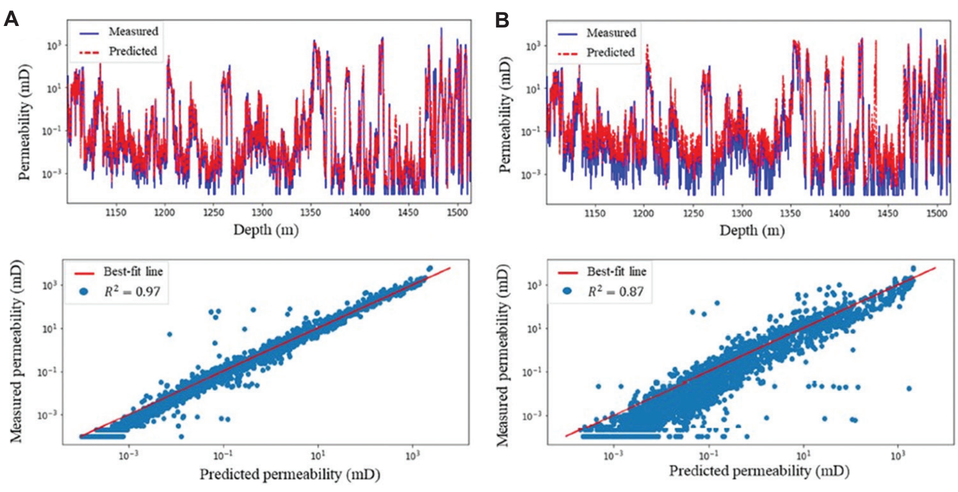

Figure 5. Measured and predicted permeability comparison. (A) Permeability prediction employing elastic properties and porosity as input features via the LightGBM modeling. (B) Elastic property-exclusive permeability prediction using the XGBoost framework. Top panels indicate depth-domain permeability profiles, while bottom panels illustrate cross-plots of predicted and core-calibrated permeability values. Reprinted from Riyadi *et al.*[46]

These methods simplify the prediction process to mathematical approximations, failing to construct genuine geologically process-driven models. The so-called "optimal feature combination" essentially represents over-adaptation to known geological conditions in training well areas. It is a feature mapping established through statistical correlations. When extrapolated to undrilled regions or complex diagenetic reservoirs, the geological plausibility of predictions becomes significantly questionable due to the absence of quantitative constraints on pore-throat network parameters. Furthermore, the inherent small-sample dilemma in reservoir parameter prediction inevitably subjects single-task learning to dual challenges of insufficient sample size and overfitting.

4.2. Data- and model-driven approaches

In 2019, Bergen *et al's*.[47] seminal review in *Science*, "Machine learning for data-driven discovery in solid earth geosciences," systematically evaluated applications of data-driven AI in solid earth sciences. The study emphasized that AI implementation must advance beyond simplistic applications to address complex geoscientific challenges. It highlighted that critical factors, such as training test set partitioning and validation methodology, significantly influence prediction outcomes. Traditional geophysical approaches typically formulate mathematical approximations between characterization parameters based on theoretical assumptions, resulting in deterministic physical models. Data-driven methods bypass theoretical presuppositions by directly extracting implicit patterns from data, making them well-suited for complex geological studies. However, they often lack physical interpretability. On the other hand, physical models offer stronger explanatory power, but they face limitations in accounting for geological complexity due to inherent assumptions and difficulties in defining inter-parameter relationships, ultimately constraining predictive accuracy. Recently, interdisciplinary collaboration has integrated data-driven methods with physical models. This integration has emerged as a promising avenue. It is deemed capable of yielding more universally applicable solutions to geophysical problems.[48-50]

The capillary bundle model provides the fundamental basis for studying fluid flow in porous media, representing the most essential physical model for permeability characterization. Its extension, the Kozeny-Carman equation, establishes the foundational relationship between porosity, pore-scale geometry, and permeability:[51]

$$\kappa = B\frac{\phi^3}{(1-\phi)^2}d^2 \tag{XIV}$$

where κ represents permeability, ϕ represents porosity, d denotes pore scale (characteristic pore/grain size), and B is a geometric factor. On this basis, Bourbie *et al*.[52] proposed a practical formulation for application to natural materials, suggesting an empirical geometric factor n is 4 or 5, which may better represent common geological media:

$$\frac{\kappa}{d^2} \propto \phi^n \tag{XV}$$

Shi *et al*.[53] incorporated pore-scale effects by calibrating n with well-log data, replacing Bourbie's proportionality with an explicit equality:

$$\frac{\kappa}{d_e^{\,2}} = \phi^n \tag{XVI}$$

Where d_e represents the equivalent pore scale. To implement this permeability model, the authors first predicted porosity through sensitive parameter analysis. They used bulk modulus, shear modulus, and density with kernel Bayesian discrimination. Subsequently, they estimated the equivalent pore scale from compressional wave velocity, shear wave velocity, and the derived porosity using the same statistical method. Finally, permeability was calculated through the porosity-equivalent pore scale-permeability relationship using seismic elastic parameters. While this method introduces valuable physical constraints to data-driven prediction, there are two key limitations: on the one hand, the permeability model accounts for pore scale and porosity effects but neglects pore morphology influences. On the other hand, cumulative errors may significantly compromise prediction accuracy. These errors arise from the stepwise porosity-pore scale-permeability calculation.

Indeed, issues such as small sample sizes and overfitting are frequently encountered in the context of distributed computational cumulative errors and reservoir parameter prediction. At present, multi-task learning addresses these challenges by establishing end-to-end learning mechanisms and sharing feature information across different tasks. This approach effectively mitigates the overfitting often associated with single-task learning, thereby enhancing the generalization capability of the network model. However, since multi-task learning relies on cross-task feature transfer to enable information interaction, the correlation between tasks plays a decisive role in model performance.

A large amount of statistical data demonstrated a close correlation between porosity and permeability. Based on this, Wei *et al*.[54] proposed a seismic prediction method for reservoir permeability using multi-task learning. The method employed post-stack seismic data and P-wave impedance as network inputs, with well-log porosity and permeability serving as labeled data of the network. Through network training, an optimal network model was established by integrating near-well seismic and well-log data. Finally, reservoir porosity and permeability parameters between wells were simultaneously predicted. Application results from the tight gas reservoir in the Shaximiao Formation of Jinqiu Gas Field, Sichuan Basin, demonstrated high consistency between predicted permeability parameters of Sand Body No. 8 and actual drilling data, along with superior vertical and horizontal resolution.

4.3. Challenges of AI-based methods

While data-driven AI models demonstrate empirical efficacy in permeability prediction, their core limitation stems from divorcing mathematical approximations from underlying petrophysical mechanisms. This physics-agnostic approach manifests as an inability to construct genuine geological process-driven models, vulnerability to local overfitting through statistically derived feature mappings, and geologically implausible extrapolation in undrilled/complex diagenetic settings due to unconstrained pore-throat parameterization.

5. Discussion

This review synthesizes the fundamental limitations inherent in the three dominant methodologies within the reservoir permeability prediction domain (Table 5).

Based on these findings, the above limitations unequivocally indicate the necessary direction for next-generation models. These models must transcend empirical curve fitting through deep integration of multiscale physical mechanisms, quantitative pore structure characterization, and physics-embedded AI architectures. Ultimately, this integration will dismantle the barriers between data-driven and physical models to achieve a paradigm shift.

Future development must focus on establishing a new permeability prediction paradigm centered on the synergistic optimization of "physical mechanism, data-driven approach, and engineering validation" (Figure 6):

(i) Theoretical mechanism innovation
   a. Develop coupled models integrating pore, fluid, and fracture system interactions with dispersion/attenuation signatures, deepening the coupled flow and elasticity theory for multi-porosity media (e.g., pores, vugs, and fractures).
   b. Advance pore-throat topology-constrained rock physics models to quantify the control weights of tortuosity and connectivity on permeability.

(ii) Data-driven architecture enhancement
   a. Construct multimodal physics-guided learning networks by fusing multi-source data (e.g., seismic attributes, electrical imaging, and nuclear magnetic resonance).
   b. Employ deep generative adversarial models to synthesize geologically realistic virtual samples (e.g., generating low-frequency signals to extend bandwidth and compensate for flow capacity calculations), thereby overcoming the bottleneck of scarce training data.

(iii) Deep embedding of physical mechanisms
   a. Deeply embed differentiable forms of fundamental physical laws (e.g., Darcy's law and Biot's theory) within neural networks.
   b. Develop cross-scale physics-informed neural networks to couple microscopic pore network simulations with macroscopic seismic responses.

(iv) Engineering validation framework
   a. Digital rock core simulation validation: Compare seismically inverted permeability against direct flow simulation results on the pore network to utilize computerized tomography scans/process-based modeling to create digital rock cores and validate the microscale mechanistic soundness and scale-transition capability of models.
   b. Blind well testing validation: Withhold data from key geological unit representative wells (blind wells) during model training and optimization, and assess spatial generalization capability and geological scenario adaptability by analyzing prediction errors (e.g., RMSE and relative error distribution) against core analysis/well test permeability data.
   c. Dynamic production history matching validation: Embed the seismically predicted 3D permeability field into reservoir simulators, use actual production dynamics (pressure, rates, water cut, etc.) as the benchmark, and quantify improvements, such as the reduction in history matching error and the enhancement of recovery factor prediction accuracy, thereby demonstrating the practical utility for development decision support.
   d. Dynamic data-driven model evolution: Trigger incremental learning and model re-optimization on acquiring new dynamic data (e.g., new drilling/core data, production tests, and 4D seismic data) and iteratively validate the performance of the updated model on new blind wells and subsequent production periods, ensuring continuous

Table 5. Summary of three methodological categories for seismic permeability prediction

Methodology		Limitation
Dispersion and attenuation	Theoretical model inversion	(a) Non-unique solutions and inherent uncertainty (b) Significant result discrepancies across methods (c) Frequent mismatch between theoretical predictions and field data
	Velocity dispersion/quality factor	(a) Non-uniqueness in dispersion attributes from frequency-dependent AVO/AVA inversion (b) High relative error in quality factor extraction
	Fluid mobility attributes	(a) Uncertainty in optimal frequency selection (b) Low resolution of mobility attributes derived from time-frequency decomposition
Pore structure	Sun model	(a) Oversimplified pore-permeability classification using compliance factors alone; velocity data integration required (b) Overly simplistic linear porosity and permeability regression post-classification
	Facies-constrained pore structure parameters	(a) High sensitivity to seismic facies and pore structure parameters, both of which are challenging to quantify accurately (b) Multicollinearity in multivariate linear regression (c) Necessity of multi-parameter pore structure factors for permeability classification
	Dual-pore-structure parameters	(a) Uncertainty in quantitative permeability expressions due to numerous undetermined coefficients (b) Error propagation from elastic parameters in seismic inversion
Artificial intelligence	Data-driven approach	(a) Lack of physical models and theoretical constraints (b) “Small-sample” and overfitting issues in single-task neural networks for reservoir parameter prediction
	Data- and model-driven approaches	(a) Neglect of pore morphology effects in constraining physical models (b) Significant error accumulation from stepwise calculations degrades permeability prediction accuracy

Abbreviations: AVA: Amplitude variation with incident angle; AVO: Amplitude variation with offset.

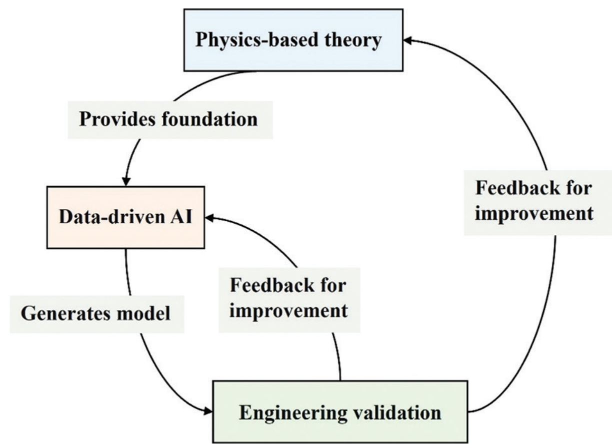

Figure 6. A proposed permeability prediction paradigm
Abbreviation: AI: Artificial intelligence.

predictive capability evolution throughout the field lifecycle.

This paradigm deeply embeds rock physics principles into neural network architectures. It achieves the unification of physical interpretability and prediction accuracy. For strongly heterogeneous reservoirs, such as fracture-vuggy carbonates and bioturbated sandstones, it enables reliable predictions at both exploration and development grades. Its closed-loop engineering validation mechanism provides quantifiable and iteratively improvable core technological support for intelligent oilfield development. This mechanism spans from digital rock core and blind well testing to history matching and dynamic evolution.

6. Conclusion

Reservoir permeability is critical for characterizing unconventional reservoirs and optimizing hydrocarbon recovery. However, its seismic prediction remains challenging due to the complex, non-explicit relationship between seismic responses and permeability, which is governed by multifaceted controlling factors. These challenges are specifically manifested in three dominant methodologies:

i. Dispersion/attenuation-based models, while grounded in explicit physical mechanisms, are constrained by the coupled interactions of pore, fluid, and fracture systems. This coupling leads to non-unique solutions, scale adaptability conflicts, and biases in fluid mobility characterization due to seismic bandwidth limitations.
ii. Pore structure methods (e.g., Sun’s compliance factor) suffer from quantification uncertainties, primarily due to oversimplified morphological characterization and parameters with ambiguous physical interpretations.
iii. AI-based methods often decouple mathematical approximations from rock physics principles, resulting in a vulnerability to overfitting and geologically implausible extrapolation. Although integrating physics with AI has improved accuracy, critical deficiencies remain, including inadequate pore-throat

topology differentiation, underutilization of seismic dispersion, and limited efficacy in enforcing physical constraints.

Consequently, overcoming these fundamental limitations necessitates a new paradigm centered on the synergistic integration of multi-scale physical mechanisms, quantitative pore-structure characterization, and physics-embedded AI architectures. This integrated approach is essential to achieve a paradigm shift from empirical curve-fitting to theoretically guided forecasting in permeability prediction.

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Conflict of interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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Visualization: Hao Yang
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Availability of data

Not applicable.

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