

Perspective

Reshaping geomechanical characterization of unconventional reservoirs with digital rock physics and artificial intelligence

Dingdian Yan¹, Luanxiao Zhao^{2,3}*, Fengshou Zhang⁴

¹*School of Civil and Environmental Engineering, Nanyang Technological University, Singapore 639798, Singapore*

²*School of Ocean and Earth Sciences, Tongji University, Shanghai 200092, China*

³*Shanghai Key Laboratory of Submarine Resources, Tongji University, Shanghai 200092, China*

⁴*Key Laboratory of Geotechnical and Underground Engineering of Ministry of Education, Tongji University, Shanghai 200092, China*

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Abstract:

Unconventional reservoirs are increasingly important for oil and gas production, climate mitigation and subsurface engineering, demanding more refined geomechanical characterization. Current approaches are limited by poorly resolved engineering-scale parameters and weak integration of heterogeneous multi-source data into iterative model updating. Digital rock physics and artificial intelligence offer two routes to address these limitations. Digital rock physics builds digital representations of cross-scale rock heterogeneity and uses experimentally constrained simulations to upscale stiffness, strength, damage evolution and stress-dependent deformation into parameters for wellbore-, fracture- and reservoir-scale models. artificial intelligence extracts geomechanical constraints from multi-source data, linking static characterization with dynamic reservoir responses to support iterative model refinement. These routes move unconventional reservoir characterization toward cross-scale parameterization, physics-constrained modelling and observation-updated prediction, strengthening the basis for safer resource development and complex subsurface engineering.

1. Introduction

Unconventional reservoirs are important for oil and gas development and emerging subsurface applications, from geological CO₂ storage and underground hydrogen storage to nuclear waste isolation. Yet their engineering response remains difficult to predict because drilling, hydraulic fracturing, injection and production perturb stress, pore pressure, fracture connectivity and fluid-rock interactions in reservoirs with heterogeneous pore systems and fracture networks. Geomechanical characterization is therefore needed to link rock fabric, stress state and fracture evolution to reservoir behaviour under engineering disturbance.

Geomechanical characterization of unconventional reservoirs remains limited by scale mismatch and information

underuse. Core tests directly constrain stiffness, strength and failure behaviour but are sparsely sampled, whereas geophysical observations cover larger volumes but often cannot resolve bedding interfaces, lithofacies assemblages and natural fracture networks. This leaves rock fabric, fracture architecture and stress heterogeneity difficult to translate into effective engineering-scale parameters. Meanwhile, observations from imaging, drilling, stimulation, monitoring and production capture fracture activation, pressure propagation, strain localization and flow-pathway evolution, but are commonly analyzed in separate workflows and rarely used to update geological and geomechanical models. Dynamic information on fracture growth, stress redistribution, damage evolution and reservoir connectivity therefore remains weakly coupled to static char-

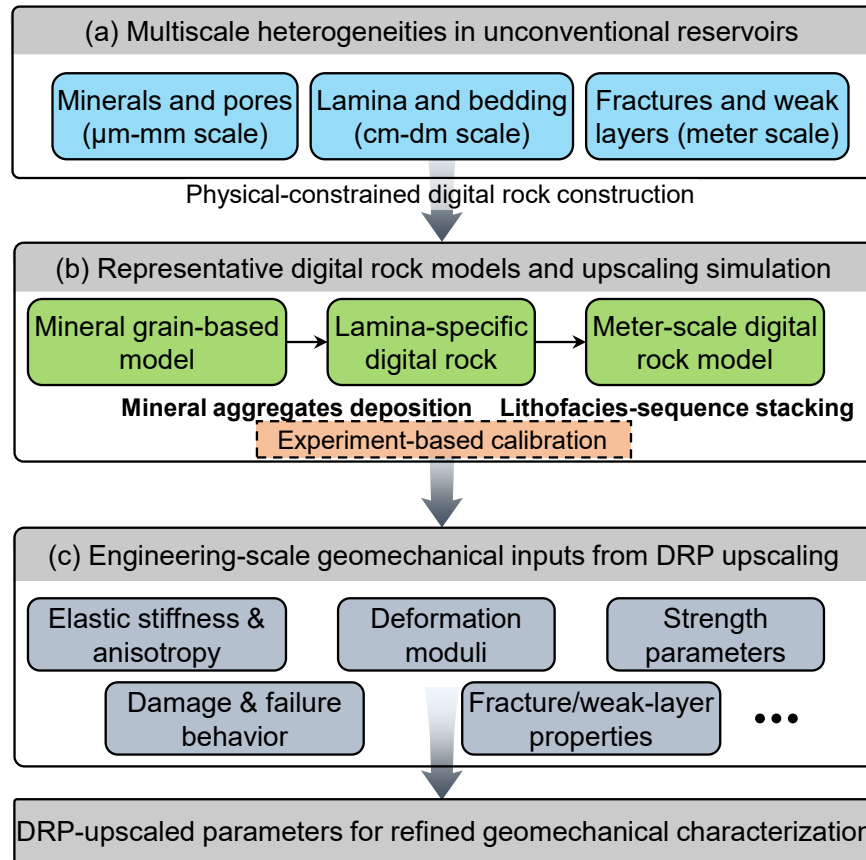


Fig. 1. Digital rock physics bridges multiscale rock heterogeneity and engineering-scale geomechanical modelling. (a) Geomechanical responses in unconventional reservoirs are controlled by scale-dependent rock structures, (b) DRP converts multiscale observations into computable digital rocks and upscales their mechanical effects through experimentally calibrated simulations, (c) the resulting effective parameters provide physically grounded inputs for engineering-scale models, improving geomechanical characterization.

acterization.

These gaps call for new routes to geomechanical characterization in unconventional reservoirs. Digital rock physics (DRP) links multiscale rock structures to engineering-scale parameters through physics-guided upscaling, whereas artificial intelligence (AI) fuses multi-source observations to extract constraints for iterative model updating. This Perspective presents DRP and AI as two routes for reshaping unconventional reservoir characterization by bridging unresolved engineering scales and enabling geomechanical models to be iteratively updated with field evidence.

2. Digital rock physics as a bridge across geomechanical scales

Geomechanical characterization of unconventional reservoirs requires effective engineering-scale properties, yet the controls on drilling, stimulation and production are rarely constrained at that scale. DRP addresses this gap by linking scale-dependent rock heterogeneity to effective geomechanical parameters. Experimentally constrained digital rocks represent pores, minerals, organic matter, bedding and microcracks in

computable form, allowing simulations to quantify how unresolved structures affect stiffness, strength, damage evolution and stress-dependent permeability (Zhao et al., 2024; Nie et al., 2025; Yan et al., 2025). These outputs provide physically grounded inputs for larger-scale models, giving DRP a stronger bridging role than empirical interpolation (Fig. 1).

The key challenge is to transfer small-scale mechanisms into wellbore, hydraulic-fracture and reservoir models as physically meaningful relations, not isolated averages. In progressive upscaling, pore-mineral models are converted into lamina- or lithofacies-scale parameters for stiffness, strength, damage and stress-sensitive permeability, then assembled according to bedding architecture, lithofacies stacking and fracture networks. Constrained by core images, mineral maps, thin sections, laboratory tests, petrophysical data and well logs, this workflow links image-based structure to effective properties across scales (Hu et al., 2023; Liu et al., 2023; Chi et al., 2024). It preserves the physical imprint of unresolved structures while removing geometric details that no longer control the response. The resulting response functions, parameter ranges and uncertainty bounds describe scale-dependent

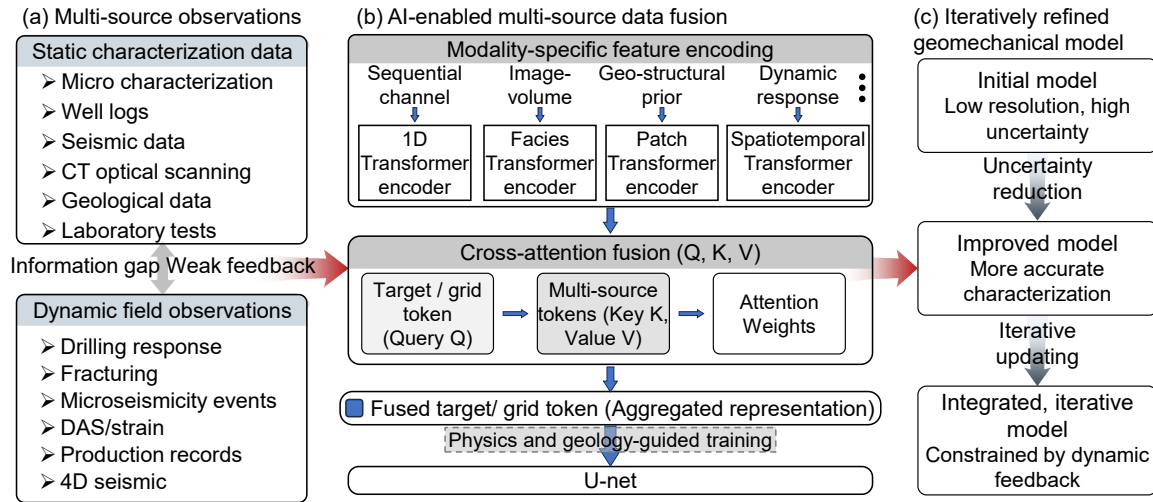


Fig. 2. AI-enabled multi-source data fusion for iterative geomechanical updating. (a) Static and dynamic observations provide complementary constraints but remain weakly coupled in conventional workflows, (b) Modality-specific Transformer encoders generate tokens that are fused by cross-attention and decoded by a physics- and geology-guided U-Net, (c) the fused outputs iteratively update geomechanical models, reducing uncertainty and improving reservoir characterization.

anisotropy, weakness-plane activation, damage accumulation and permeability evolution, providing traceable inputs for engineering-scale geomechanical modelling.

3. AI-enabled fusion for iterative geomechanical refinement

The growing observational basis of unconventional reservoirs is moving characterization beyond static descriptions toward dynamic evidence of reservoir response. Drilling, stimulation, monitoring and production now generate microseismic, distributed acoustic sensing, real-time drilling, 4D seismic and surface-deformation data that record fracture growth, strain localization, bit-rock interaction, pressure redistribution and compaction (Dinh and Van der Baan, 2019; Staniewicz et al., 2020; Bai et al., 2025). Although these observations reflect different expressions of the same evolving geomechanical system, they are still often processed separately or merged through qualitative comparison and weighted averaging. AI enables multi-source data fusion by learning shared geomechanical representations across event clouds, waveforms, logs, images and time series, allowing heterogeneous observations to constrain fracture-network development, stress perturbation, damage accumulation and flow-pathway evolution (Liu et al., 2025; Zhao et al., 2026).

AI also enables reservoir geomechanical models to move from static representations to iteratively updated descriptions of reservoir evolution (Fig. 2). Conventional workflows often rely on parameters fixed after stage-based calibration, although stimulation and production continually modify stress paths, pore pressure, fracture networks and damaged zones (Boyet et al., 2023; McKean et al., 2023). AI-enabled updating instead forms an observation-driven loop in which field data revise the inferred subsurface state, forward predictions test the re-

sion, and prediction-measurement residuals guide subsequent correction (Schultz et al., 2026). Constrained by conservation laws, constitutive behaviour and geomechanical consistency, physics-informed machine learning and fast surrogate models can support inverse modelling, parameter updating and rapid prediction (Haghighat et al., 2021; Karniadakis et al., 2021). Coupled with Bayesian data-assimilation schemes, these tools can further update evolving parameters and uncertainties, including fracture geometry, pressure-stress coupling and permeability anisotropy (Noii et al., 2021).

4. Reshaping geomechanical characterization with DRP and AI

DRP and AI address two persistent bottlenecks in unconventional reservoir characterization: scale mismatch and information underuse. DRP works upward from rock structure, using physics-guided upscaling to derive engineering-scale geomechanical parameters that are critical to drilling, stimulation, production and storage but rarely constrained directly. AI works across static and dynamic observations, extracting geomechanical constraints from heterogeneous data and using them to update reservoir models iteratively. The two routes also reinforce each other: AI can improve segmentation, generate representative digital rocks, accelerate simulations and learn mappings from digital-rock outputs to field-scale parameters, whereas digital-rock simulations can supply physics-based data and priors for AI models. Sharper reservoir characterization will therefore rely on coupling physics-guided upscaling with observation-driven updating, making geomechanical models more scale-aware, more responsive to field evidence and less dependent on isolated empirical calibration.

5. Conclusions and prospects

Unconventional reservoir characterization is shifting toward two linked tasks: deriving reliable engineering-scale geomechanical inputs and updating reservoir models as field evidence accumulates. DRP can supply physically grounded parameters that are difficult to measure directly, while AI can extract constraints from multi-source observations and feed them into iterative model refinement. Progress will depend less on data volume or algorithmic complexity than on the reliability, uncertainty and traceability of the resulting models. Priorities include stronger experimental calibration and cross-scale validation of digital-rock simulations, together with AI workflows that are uncertainty-aware, physically constrained, interpretable and explicitly linked to observations, inferred states and model updates. The long-term goal is a characterization framework in which geomechanical models are built from rock physics, corrected by field evidence and revised as the reservoir evolves.

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Conflicts of interest

The authors declare no competing interest.

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