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Quantitative Seismic Prediction of Reservoir Properties Using Rock Physics Guided Convolutional Neural Networks

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Summary

This study presents a machine learning-based seismic quantitative interpretation workflow applied to an unconventional reservoir in the Midland Basin, with an emphasis on direct prediction of reservoir and geomechanical properties from pre-stack seismic data. A novel rock physics-guided convolutional neural network (CNN) approach is used to jointly estimate elastic and petrophysical properties as well as mineral composition. The workflow addresses the need to identify mechanically brittle and hydraulically favorable intervals in the Midland Basin and provides a useful analogue to the Montney Shale in Canada, where similar challenges related to heterogeneity, brittleness assessment, and landing zone optimization are encountered.

Geology

The Midland Basin comprises a thick succession of unconventional reservoirs, including the Sprayberry, Wolfcamp, Barnett and Woodford formations, deposited in mixed siliciclastic–carbonate basinal environments that impart strong vertical and lateral heterogeneity (Bhatnagar et al., 2024). These intervals consist of finely laminated mudstones, siltstones, and thin carbonate beds with variable TOC, mineralogy, and mechanical layering, all of which influence fracability, and overall reservoir quality. Despite its different tectonic setting, this heterogeneity closely parallels that of the Montney Shale in Western Canada, where similar variations in kerogen content, brittleness, and facies architecture complicate landing-zone selection and completion design. This geological context underscores the need for integrated quantitative interpretation approaches capable of resolving fine-scale variability and identifying mechanically favorable intervals in both plays.

Method

The workflow integrates well logs, synthetic modeling, and seismic data to train CNN models capable of predicting multiple subsurface properties simultaneously (Downton and Hampson, 2021). Data from five wells are used to generate an expanded synthetic training dataset using the Keys and Xu rock physics model (Keys and Xu, 2002). Forward AVO modeling is then applied to simulate seismic responses under different lithologic and fluid conditions, generating hundreds of “what-if” scenarios that capture plausible variations in reservoir properties (Downton et al., 2020).

Two separate CNN models are trained: the first estimates porosity, water saturation, P-impedance, S-impedance, and density, from which geomechanical properties such as Young’s modulus and brittleness index are derived. The second model concurrently predicts mineral volumes including quartz, clay, calcite, and kerogen. Transfer learning is incorporated by integrating real seismic and well-log data into the workflow, improving model robustness and reducing the mismatch between synthetic and seismic responses.

Conclusions

The Midland Basin case study demonstrates that CNNs, when guided by rock physics and supported by synthetic training data, can reliably predict a broad range of elastic, reservoir, and mineralogical properties directly from seismic gathers. Generating an expanded synthetic dataset proved essential for capturing realistic variations in reservoir behavior, while transfer learning played a critical role in aligning model predictions with real seismic and log responses. The ability of the CNNs to predict multiple properties simultaneously resulted in significant efficiency gains and a more integrated view of the reservoir. Model outputs show strong agreement with well log measurements, including six blind validation wells, and clearly resolve the target interval with consistent lateral continuity. As an example, *Figure 1a-c* shows the predicted density, porosity, and brittleness index, respectively, demonstrating excellent agreement across all six blind wells within the target interval. From a development perspective, these results enhance confidence in reservoir characterization, improve understanding of heterogeneity, and support more informed drilling and completion decisions. The workflow not only reinforces the productivity of the studied intervals but also highlights its potential to identify additional development opportunities, offering a transferable framework for unconventional reservoirs such as the Montney Shale where similar geological and geomechanical challenges exist.

Novel Information

CNNs have transformed the field of computer vision by enabling machines to recognize complex spatial patterns with high accuracy. Within the geosciences, similar CNN architectures have been widely adopted predominantly for qualitative interpretation tasks, such as fault detection, facies classification, geobody detection, and automated horizon tracking where the primary objective is pattern recognition. The novelty of this work lies in extending CNN-based methodologies beyond qualitative interpretation to achieve quantitative reservoir characterization directly from seismic data. By integrating rock physics constraints, synthetic modeling, and well calibration, the proposed workflow enables CNNs to predict continuous elastic, petrophysical, geomechanical, and mineralogical properties in a physically consistent manner. This shift from image-based qualitative interpretation to quantitative property estimation represents a significant advancement in the application of deep learning for subsurface characterization and supports more objective, data-driven decision making in unconventional reservoir development.

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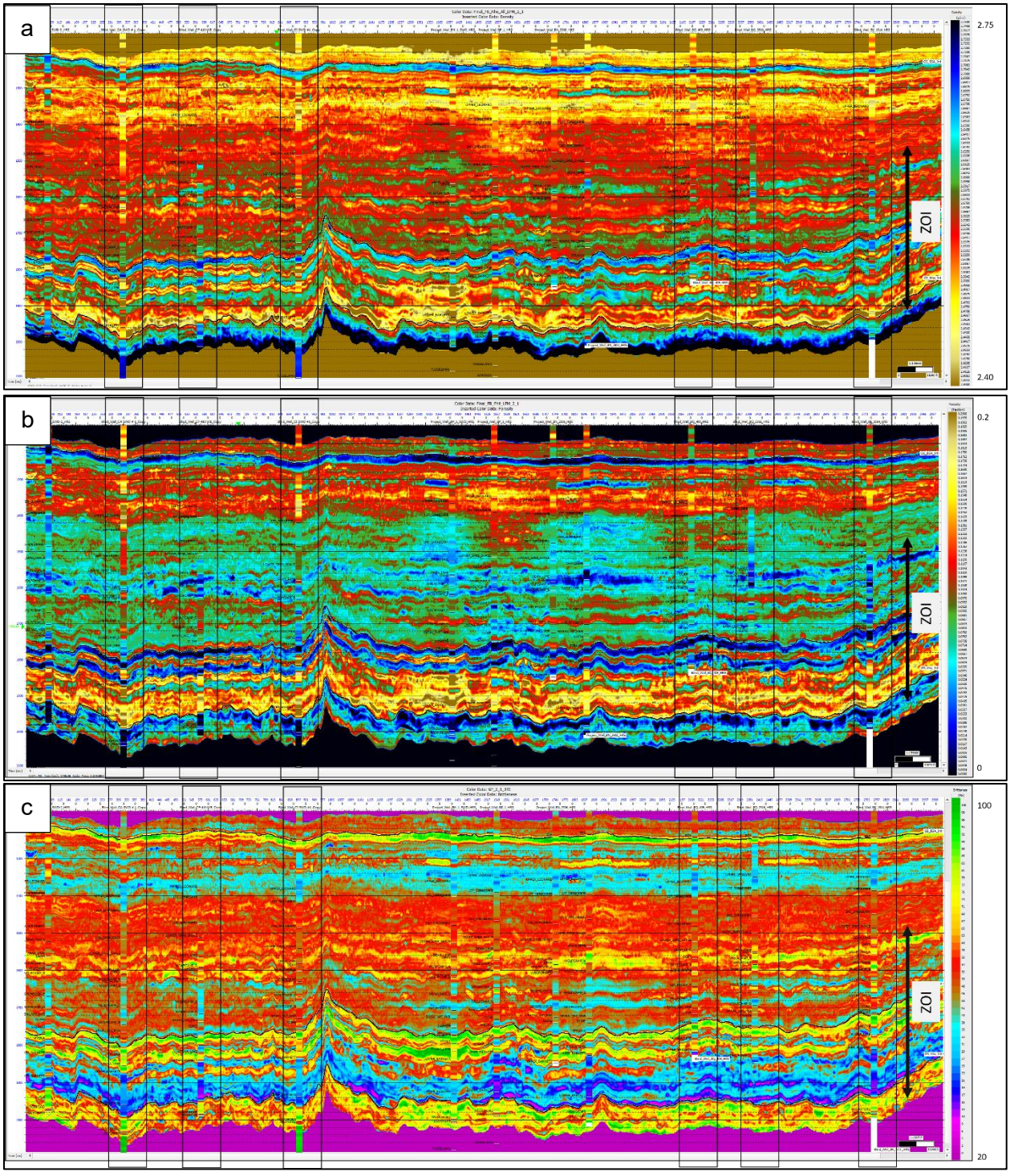


Figure 1: a) Predicted density b) predicted total porosity and c) estimated brittleness index. Black rectangles indicate true blind wells. The approximate Zone of Interest (ZOI) is marked with an arrow.

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