

Mud barriers/baffles and lean zones identification in oil sands reservoir through joint PP-PS pre-stack seismic inversion, neural network, and Bayesian classification

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Summary

Understanding the spatial variation of lithology and fluid composition and identifying mud barriers/baffles and lean zones from oil sands reservoirs is crucial for pad planning and well placement of a Steam-assisted Gravity Drainage (SAGD) project.

In this study, we present a workflow that integrates seismic data, well data, and geological information with several seismic prediction approaches to characterize very complex heterogeneous features (e.g., identifying mud barriers/baffles and lean zones) in the Athabasca oil sands. The workflow includes 5 steps:

- First, cross-plotting analysis was used to determine the sensitivity of various elastic properties to reservoir properties; V_p/V_s ratio and density show a higher correlation with lithology and fluid type.
- Second, target-oriented seismic data conditioning was done to enhance the signal-to-noise ratio, preserve AVO amplitude variation, and expand the useful angle range; After data conditioning. The useful angle range has expanded from ~30 degrees to ~40 degrees for the PP gathers, and from ~50 degrees to ~60 degrees for the PS gathers. The overall well-to-seismic tie has been improved, which greatly reduced uncertainty for elastic estimates requiring a large angle range (e.g. >45 degrees for density and >32 degrees for shear velocity).
- Third, multi-component (PS) data was incorporated into inversion processing, resulting in a significant improvement in V_p/V_s ratio and S-impedance (from ~70% to 85%), and density estimates (from ~70% to 80%), as well as noticeable improvement for other elastic properties compared to inversion with PP data only.
- Fourth, a statistical multi-attribute Regression (MAR) method was applied to refine and improve the vertical resolution of the key attribute estimates. Some small (beyond seismic band-limited) features were identified through this step.
- Finally, Bayesian lithology and fluid classification were performed to differentiate lithology (e.g., sand, IHS, mud, coal, paleo) and fluid types (e.g., oil, lean, water), as well as associated probability distribution functions (PDF), thereby quantifying the uncertainty for lithology and fluid prediction.

We compare and validate the inversion and MAR results at 28 new strat well locations in the study area using Pearson's cross-correlation analysis. The correlation coefficient between seismic estimates and well measurement for all key elastic properties (such as density, V_p/V_s ratio) is greater than 80%.

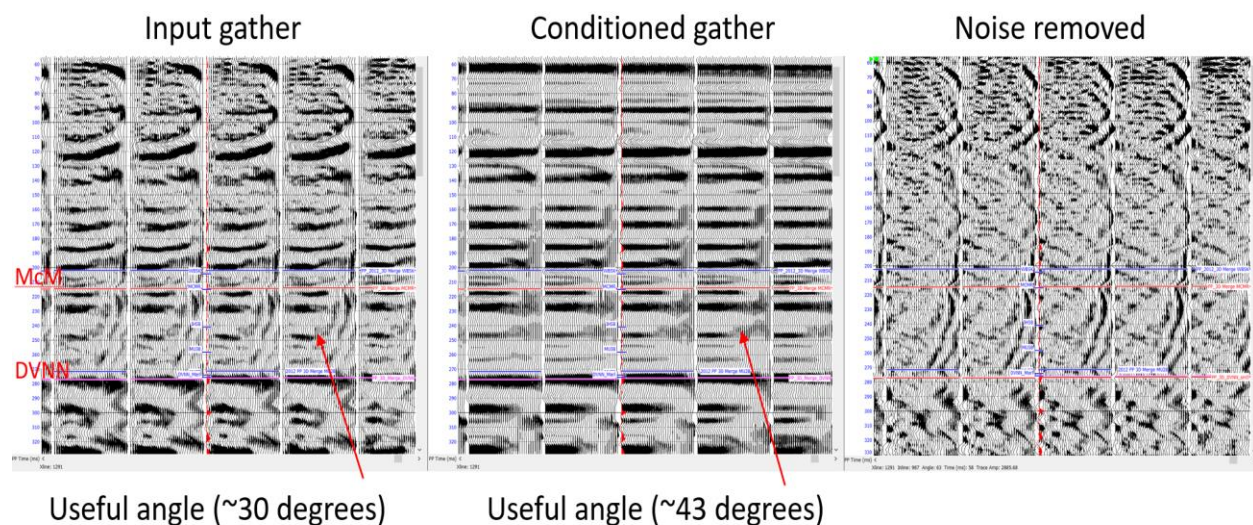
As a result, we have successfully differentiated mud (with 85% confidence) from sand, IHS/breccia, and coal; there is less than 15% overlap between sand and mud classes; and less than 20% confusion between sand and IHS/breccia or coal. Moreover, lean zones, with thicknesses greater than 3 m, were effectively distinguished (with greater than 75% confidence) from oil.

Predicted lithology and fluid volumes were well-matched with actual lithology and fluid logs at both existing wells and the 28 new wells. The accuracy of lithology and fluid prediction will significantly increase the confidence in further reservoir development in this area. In addition, associated probability cubes provide a quantitative assessment of the uncertainty for risk management.

Results at blind wells (red stars)

1. Seismic data conditioning before and after (Figure 1)

(a) PP data conditioning example



(b) PS data conditioning example

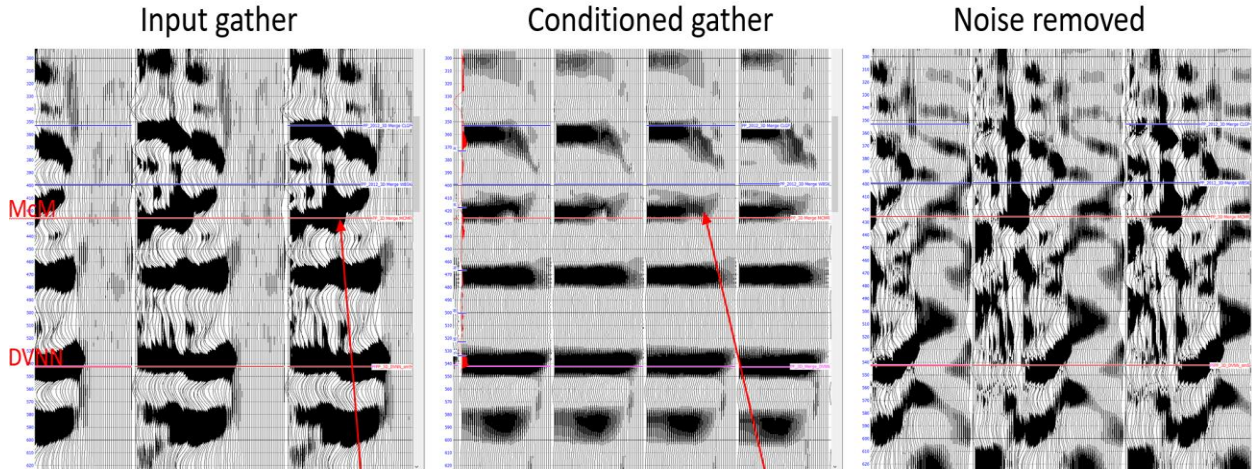


Figure 1. Input and conditioned angle gathers for joint PP-PS inversion. (a) PP gather conditioning example, (b) PS gather conditioning example. In each case, the input angle gathers are shown in the left frame, the conditioned gathers are shown in the middle frame, and the difference between the two is shown to the right. Data conditioning was found to enhance the signal-to-noise ratio, preserve AVO amplitude variation, and expand the useful angle range from ~30 degrees to ~43 degrees for the PP data, and from ~ 50 degrees to ~ 60 degrees for the PS gather. The overall well-to-seismic tie has been improved.

2. Joint PP-PS versus PP pre-stack inversion at blind wells (red stars, Figure 2)

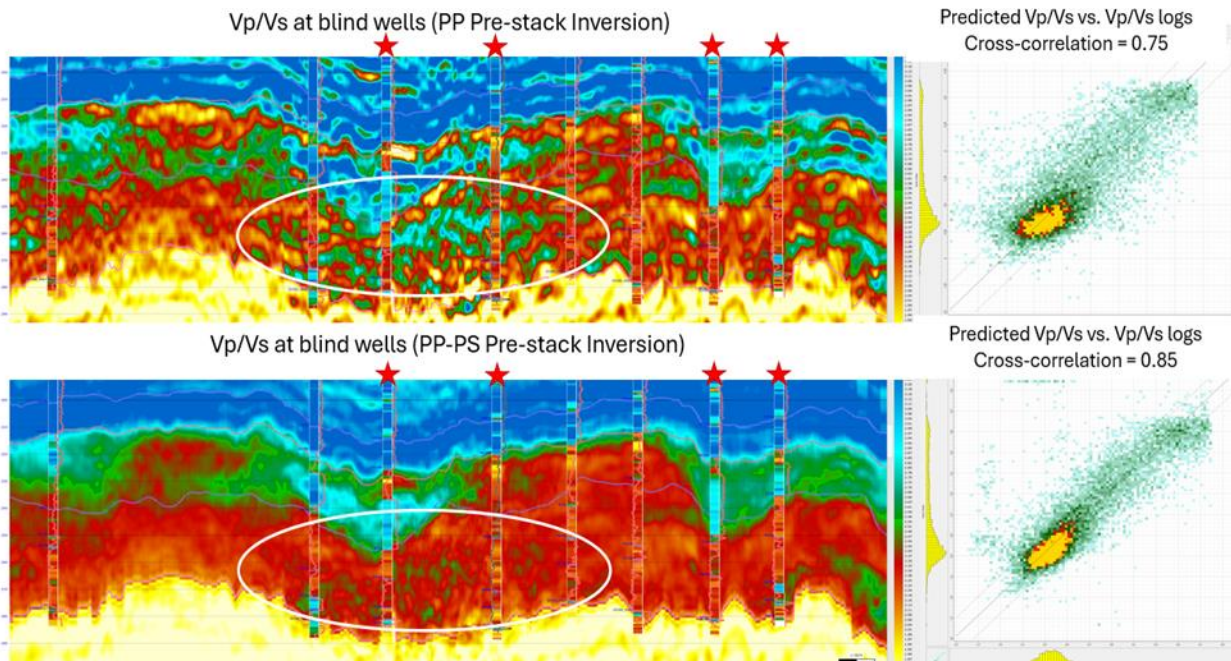


Figure 2. Comparison of the inverted V_p/V_s ratio at 4 blind wells (red stars) from the PP pre-stack inversion method (top), and joint PP-PS pre-stack inversion method (bottom); the inverted V_p/V_s ratio is superimposed with corresponding well-logs in color and gamma-ray in the curve at well locations within 50 m. Cross-correlation analysis between inverted attributes and measured well logs from 40+ wells at the well location shown on the right.

3. Neural network versus Joint PP-PS inversion at blind wells (red stars, Figure 3)

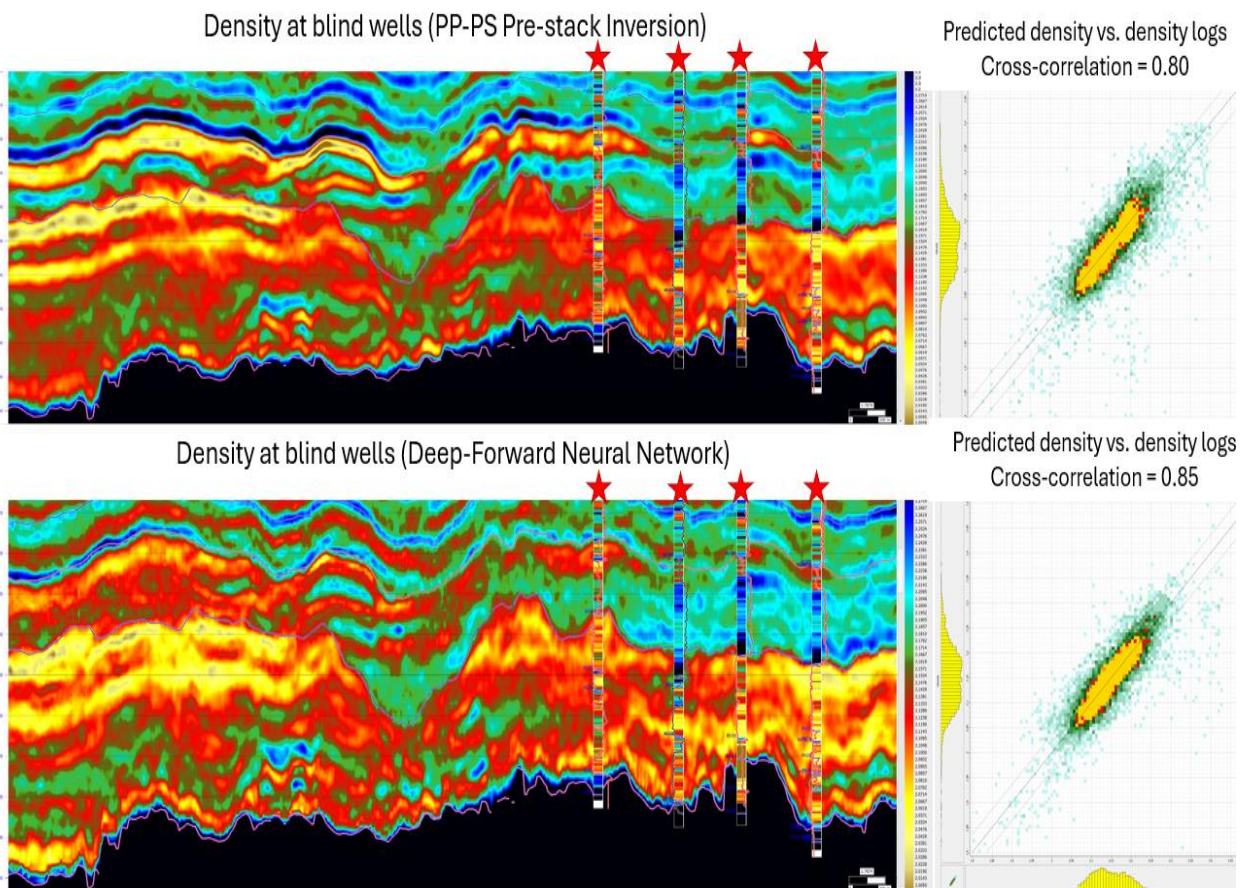


Figure 3. Comparison of density estimated at blind wells (red stars) by two methods. Density predicted from joint PP-PS pre-stack inversion method (top), and neural network method (bottom); the inverted density is superimposed with measured density logs in color and gamma-ray in the curve at well locations within 50 m. Cross-correlation analysis between inverted attributes and measured corresponding well logs from 200+ wells at the well location is shown on the right. Notice that the correlation coefficient has improved from 80% (using joint inversion) to 85% (with the MAR method), and some detailed heterogeneous features were observed through the MAR results, which were not otherwise discernible from joint inversion.

4. Bayesian lithology and fluid classification at blind wells (red stars, Figure 4)

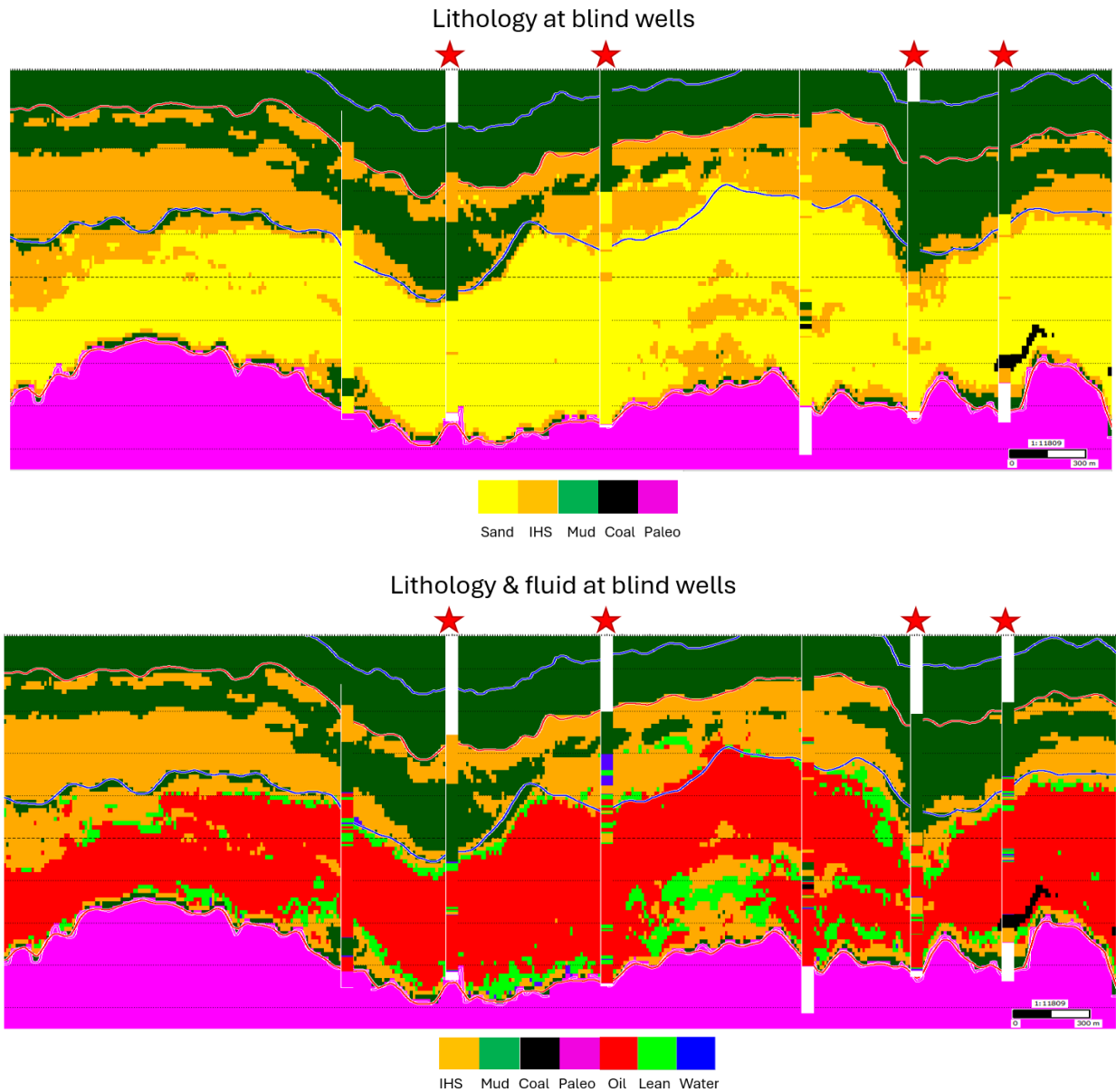


Figure 4. Predicted lithology and fluid volumes at 4 blind wells (red stars). The predicted lithology-fluid superimposed with lithology-fluid logs (using the same colors) at well locations within 50 m. The predicted lithology-fluid shows a good match with lithology-fluid logs. The lean/water zones, with thicknesses greater than 3 m were effectively distinguished from bitumen oil with greater than 75% confidence.

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