geoconvention
Calgary • Canada • May 11-13 2026

Thinking Fast and Slow: A Comparison of EEI and Pre-stack Facies-Based Seismic Inversion with Application to Onshore Colombia

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Summary

Characterizing the subsurface with seismic data can be accomplished with both fast-track and full pre-stack seismic inversion workflows. Each method has an associated time and complexity that geoscientists need to balance with project goals. We compare the results from running a rapid EEI (Extended Elastic Impedance) characterization of porosity and clay content with a more extensive pre-stack facies-based inversion followed by machine learning workflow. The comparison is made over a producing property in the Llanos Basin, Colombia. The results provide some insight into the benefits and disadvantages of each method, relating to the impact of geologic constraints to improve the sand/shale prediction in an environment with variable seismic quality.

Workflow

Subsurface characterization from seismic data can be accomplished through a variety of approaches. This most straightforward is post-stack amplitude mapping, and in order of increasing complexity choices include pre-stack AVO classification, pre-stack relative inversion, simultaneous inversion, facies-based inversion and geostatistical inversion. Considerable variation in approaches within these categories exist, but the common trend is an increasing use of additional data and geologic constraints to resolve ambiguity and provide a more complete subsurface interpretation. In addition, post-processing is commonly applied to elastic attributes to provide best estimates of reservoir properties through machine learning. This represents another layer of complexity in which non-linear relationships can be leveraged to improve the accuracy of the reservoir outputs. All additional complexity takes time, and it is instructive to contrast the results from different approaches.

For a rapid analysis, we employ the Extended Elastic Impedance (EEI) approach of Whitcombe and Connolly (2002). This workflow is an extension of pre-stack AVO classification in that it limits the analysis to acoustic impedance (AI) and gradient impedance (GI), rather than the standard three elastic parameters output from a full pre-stack inversion. EEI inversion is usually run as a relative 'coloured' inversion (Lancaster and Whitcombe, 2000) omitting construction of the somewhat interpretive low-frequency component of the elastic properties. To highlight subsurface properties of interest, the workflow involves choosing a linear combination of the relative impedances (rAI and rGI) that maximally correlate with the property of interest, such as porosity. Through a series of fairly rapid steps, an interpreter can therefore prepare a 3D band-limited volume that correlates to some extent with subsurface reservoir properties. For the Llanos Basin data set, we choose total porosity and volume of clay as two desirable quantities to characterize potential drilling targets.

For a more comprehensive analysis, we employ a facies-based pre-stack inversion (Kemper and Gunning, 2014, Gunning and Sams, 2018). This pre-stack inversion is characterized by defining a discrete set of lithologies (elastic facies) and their associated property depth trends to represent the possible elastic variation found in the subsurface. This approach, in essence, employs known geologic constraints to manage the challenges presented by seismic resolution and noise. The outputs from this inversion (AI and Vp/Vs ratio) are then combined with deep neural network (DNN) mapping (Murphy, 2012) to produce 3D estimates porosity and VClay. The use of facies classes in the seismic inversion, as well as the use of machine learning in the post-processing represents a *non-linear* estimation of reservoir properties from seismic data, in contrast to the EEI approach which represents a *linear* transform. As we shall see, this non-linearity introduces frequencies that are not present in the input data, both high and low that are in part derived from the band-limited seismic data.

Results

The Llanos Basin in Colombia contains well-consolidated estuarine sandstones in the Eocene and Paleocene that are targets for oil and gas development. Our inversion workflows were preceded by log preparation and facies assignment, as well as a seismic conditioning phase to prepare the data for quantitative interpretation. The log data was of variable quality, with adverse borehole conditions interfering in places with log measurements. The seismic data was also of mixed quality with multiple contamination and fault zones creating primary signal interference.

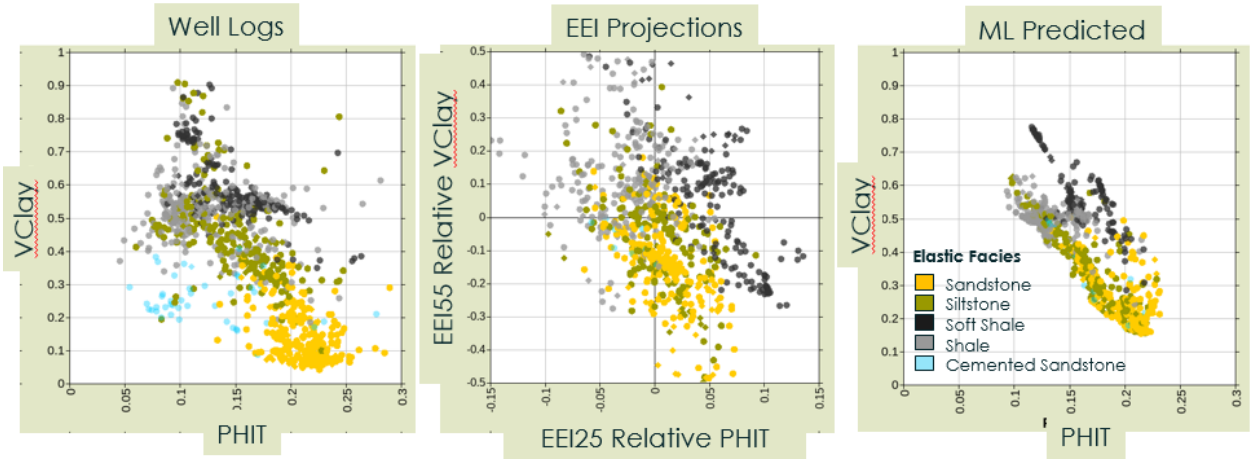


Figure 1: Porosity and VClay cross-plots olured by facies.The left plot shows the well logs while the middle plot is band-limited projections (EEI25 and EEI55) from well logs and the right plot shows machine learning porosity and VClay using AI and Vp/Vs well log inputs. Facies are exact in all plots.

Figure 1 shows well log petrophysics (left) and EEI predictions (center) and DNN prediction (right), both employing the well log elastic properties to illustrate in advance what may be possible to image from seismic using the EEI and full facies inversion / ML property estimation workflows in the absence of noise. The linear EEI elastic properties have been shaped by a 4-8-100-110Hz Ormsby filter, consistent with the frequencies that were chosen for the coloured inversion operators. The EEI projections show more scatter in facies clustering as is expected from a linear approach, but discrimination of sands appears possible.

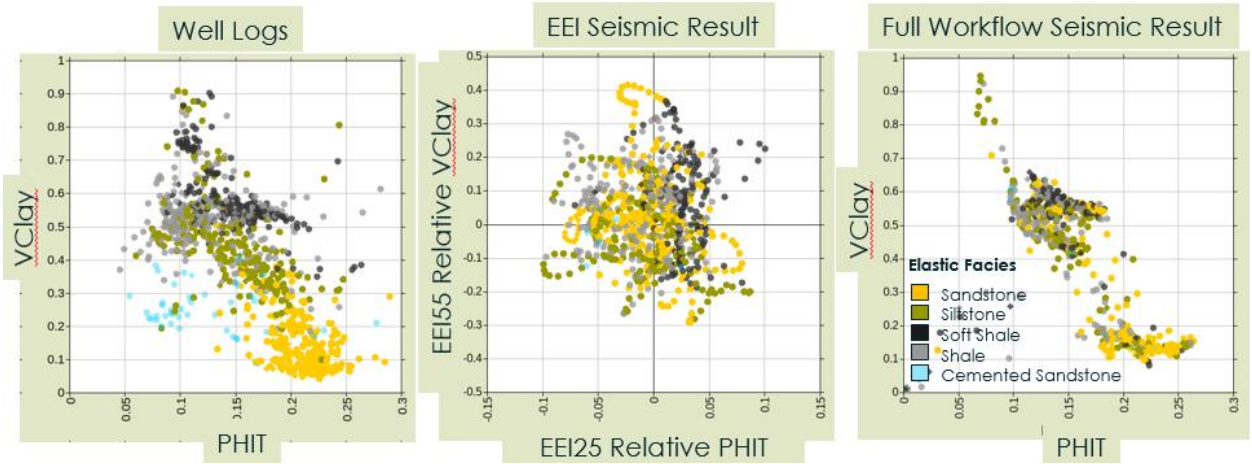


Figure 2: Porosity and VClay cross-plots colured by facies.The left plot shows the well logs while the middle plot shows EEI projects extracted at wells, coloured by exact (well) facies. The right plot are the extractions from seismic PHIT and VClay volumes at wells following the full workflow.

The results of the property predictions from seismic were extracted at eight wells and plotted in Figure 2. The full workflow results (right) appear reasonable relative to the well log data (left). The EEI projections (center) appear to have little merit. However, a different conclusion can be reached when viewing the results in 2D as shown in Figure 3 (top). The upper part of the Eocene reservoir is poorly imaged by the EEI VClay estimate, with AVO gradients having been compromised by interference at the top of this reservoir. Nevertheless, these relative properties surprisingly point to the existence of shales that are verified by comparison with the wells. The lower Paleocene reservoir is better imaged by the EEI VClay projection, and we see a good correlation with the sands at the wells. Figure 3 (center) is the VClay prediction from the full workflow, bandlimited with the 4-8-100-110Hz Ormsby filter corresponding to the coloured inversion EEI operator. We see a much sharper definition of sand boundaries where the facies-based inversion has generally increased the definition of the sands and shales while also correcting the VClay estimates in the Eocene. However, the improved property definition that accompanies the assignment of facies, responds to the dominant signal present, possibly overlooking subtler signal expressions that may be interpreted. For example, the yellow arrows near well C point to shales (confirmed by the well) that have a longer extent in the EEI VClay volume than in the full workflow interpretation. Figure 3 (bottom) shows the corresponding full-band result with low frequencies enabling a good match of well log VClay values. Note that the wells are not used in the inversion directly for either workflow. Base Eocene erosive channels can clearly be seen in the maps in Figure 4 (top left). EEI indicates these are high porosity and mid-high clay content (top right) caused by an ambiguous AVO signature at these locations where GI lacks the resolution of AI. Applying the DNN porosity prediction to the full workflow elastic properties, *without* facies, interestingly produces high porosity channels surrounding a clay rich core, aligning with the EEI VClay interpretation. Upon inclusion of the inverted facies, the channels become high porosity (bottom right) confirmed by well penetrations. This is a good example of prior lithology constraints overruling an unlikely assignment of properties, which an EEI interpreter must keep in mind.

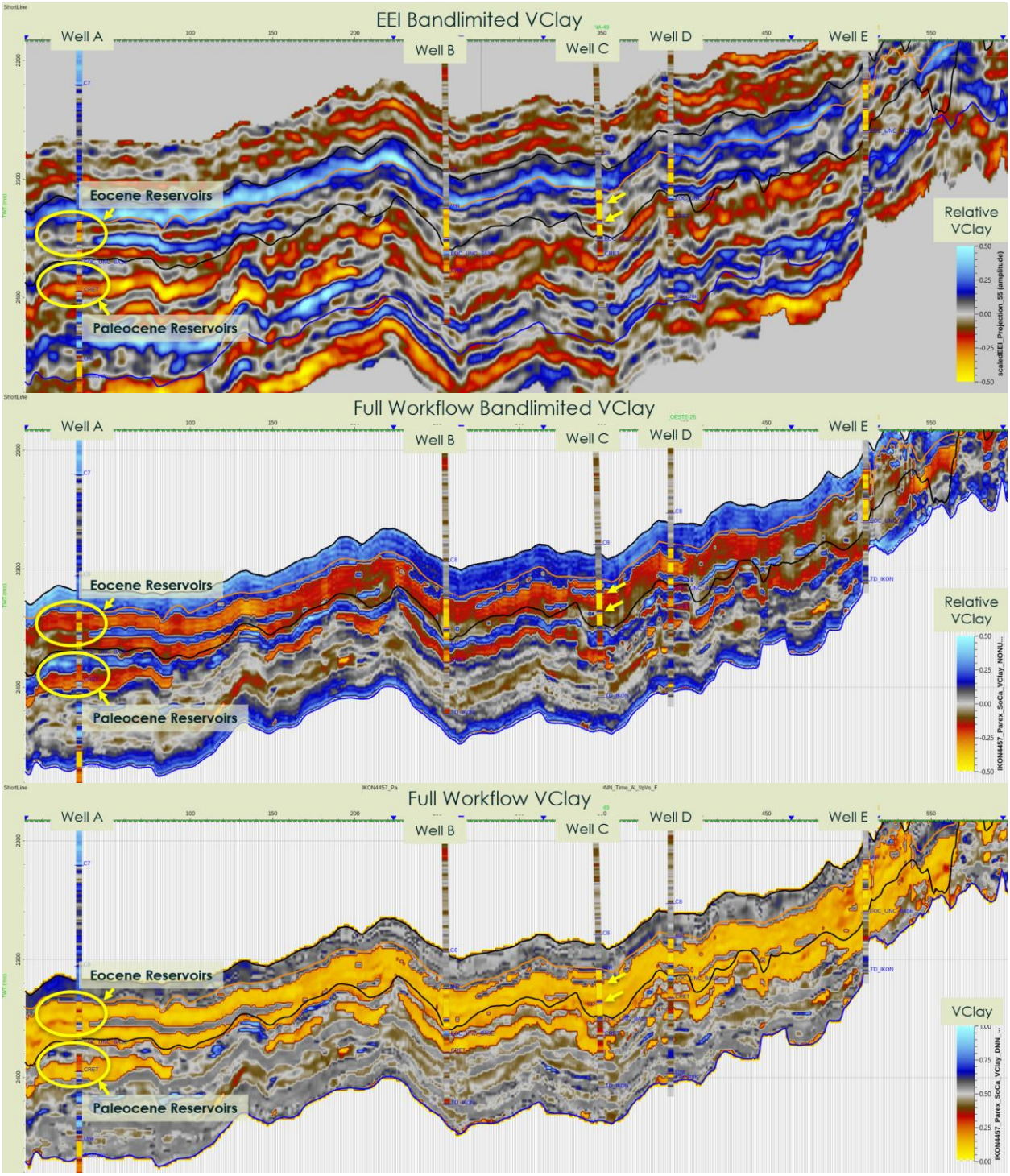


Figure 3: EEI VClay projection (top), bandlimited full workflow VClay (middle) and full workflow VClay (bottom). The well logs shown are all full-band VClay.

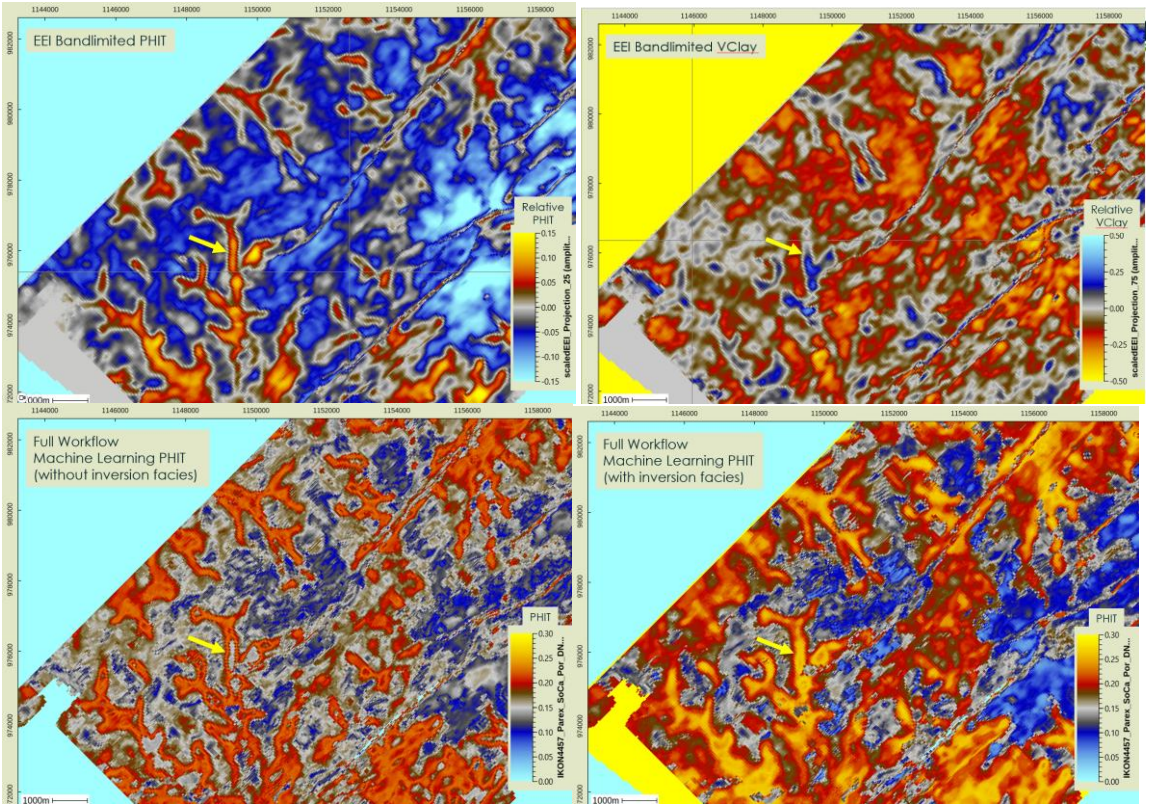


Figure 4: Horizon amplitudes near the base Eocene of the EEI porosity (top left), EEI VClay (top right) and full workflow porosity omitting facies from ML porosity prediction (bottom left) and final full workflow porosity results (bottom right).

Additive Information

We have shown an example of a fast-track inversion with a more elaborate facies-based inversion and machine learning workflow that helps geoscientists gauge the potential risks and rewards of employing both approaches, allowing better informed characterization decisions to be made.

Acknowledgements

We would like to thank Franck Delbecq and Parviz Ajourlou for project assistance and Parex Resources for permission to publish these results.

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