

Integration of Bayesian AVO inversion and statistical rock physics using elastic-FWI-informed models: an application to Agogo field, Angola

Introduction

In seismically constrained reservoir characterization, statistical rock physics combines statistical techniques with physical equations to relate elastic attributes (velocities, impedances, density) to petrophysical properties (porosity, clay content, water saturation). Because this physical link is affected by uncertainty from rock heterogeneity, measurement errors, model approximations, and scale differences, the estimation of reservoir petrophysical properties from seismic data is formulated as a Bayesian inverse problem.

The traditional statistical rock-physics workflow first establishes deterministic petroelastic relations and then converts them into probabilistic transformations through Monte Carlo simulation, capturing both natural variability and model inaccuracy (Mukerji et al., 2001; Eidsvik et al., 2004; Avseth et al., 2005) and has been integrated in Bayesian inversion workflows for seismic reservoir characterization (Grana and Della Rossa, 2010; Paparozzi et al., 2011; Grana et al., 2017). However, this approach generally requires the knowledge of the rock physics model formulation, which is not always available, and it is often difficult to calibrate. Hence, we propose a method that integrates data-driven statistical rock physics with Bayesian linearized seismic inversion to estimate the full probability distributions of petrophysical variables and litho-fluid classes directly from prestack seismic data.

The proposed approach is based on three components: (1) the use of more flexible probability models such as Gaussian Mixture Models (GMM) to overcome the limitations of single-Gaussian assumptions; (2) the explicit treatment of the upscaling problem, embedding the change of scale between log and seismic resolution within the probabilistic framework; and (3) a fully Bayesian propagation of uncertainty across three sequential steps: linearized seismic inversion, probabilistic upscaling, and petrophysical inversion. This workflow is applied to seismic OBN data where results of elastic full waveform inversion (E-FWI) are used as a prior model for the Bayesian inversion workflow. The use of E-FWI allows integrating a prior model with higher frequency content compared to traditional AVO inversion and is directly conditioned from well log data. This approach is demonstrated on a dataset acquired in the Agogo field, offshore Angola.

Method

The method estimates the posterior probability of petrophysical properties $\mathbf{R}$, for example porosity, water saturation, and clay content $\mathbf{R} = [\phi, s_w, C]$, and litho-fluid classes π conditioned on AVO seismic data $\mathbf{S}$, by combining three conditional probabilities in a single Bayesian workflow: $P(\mathbf{m}_c|\mathbf{S})$, $P(\mathbf{m}_f|\mathbf{m}_c)$, and $P(\mathbf{R}|\mathbf{m}_f)$, where $\mathbf{m}_c$ and $\mathbf{m}_f$ represent the elastic properties (for example impedances $\mathbf{m} = [I_p, I_s]$) at the coarse (seismic) and fine (well log) scales. The method is implemented in a proprietary software organized in three steps.

Bayesian linearized AVO inversion. Elastic properties are first inverted from partial-angle stacks using the linearized Bayesian AVO inversion (Buland and Omre, 2003), which combines the convolutional model with the Aki-Richards approximation: $\mathbf{S} = \mathbf{G}\boldsymbol{\ell} + \mathbf{e}$, with $\boldsymbol{\ell}$ a log-Gaussian prior on elastic parameters and $\mathbf{e}$ Gaussian noise. The posterior $P(\boldsymbol{\ell}|\mathbf{S})$ is analytically Gaussian, yielding a log-normal distribution $P(\mathbf{m}_c|\mathbf{S})$ at each depth.

Probabilistic upscaling. Because well-log and seismic data are at different resolutions, fine-scale elastic samples $\mathbf{m}_f$ are upscaled to coarse scale $\mathbf{m}_c$ via Backus averaging (for velocities) and linear averaging (for density), applied with a running window whose length is derived from the seismic wavelength. The joint sample set $\{\mathbf{m}_f, \mathbf{m}_c\}$ then allows estimation of $P(\mathbf{m}_f|\mathbf{m}_c)$.

Statistical rock-physics modeling. A rock-physics model $\mathbf{m}_f = f_{RPM}(\mathbf{R}) + \varepsilon$ links petrophysical variables to elastic attributes $\mathbf{m}$, where ε is a zero-mean Gaussian error describing model inaccuracy, with covariance estimated from well-log data. The rock physics model can be based on theoretical relations (physics-driven) or on well log data (data-driven). In the data-driven approach, the statistical rock physics model is implicit and estimated from well logs. The prior distribution $P(\mathbf{R})$ is assumed to be a multivariate Gaussian Mixture with n components, one per litho-fluid class, whose weights correspond to the indicator probabilities of the classes. The joint distribution $P(\mathbf{m}_f, \mathbf{R})$ is estimated using the Expectation-Maximization (EM) algorithm for GMMs, yielding closed-form conditional means and covariances of $P(\mathbf{R}|\mathbf{m}_f)$.

The final posterior of petrophysical properties is then computed using the Chapman Kolmogorov integral: $P(\mathbf{R}|\mathbf{S}) = \int P(\mathbf{R}|\mathbf{m}_f)P(\mathbf{m}_f|\mathbf{m}_c)P(\mathbf{m}_c|\mathbf{S})$. For discrete classification, the posterior of litho-fluid classes is computed as $P(\pi|\mathbf{S}) = \int P(\pi|\mathbf{R})P(\mathbf{R}|\mathbf{S})$. This framework therefore propagates multiple uncertainty sources, such as rock heterogeneity, rock-physics model inaccuracy, scale change, and seismic noise, into a coherent posterior describing both continuous reservoir properties and discrete facies. In Figure 1, we show the schematic workflow of the inversion.

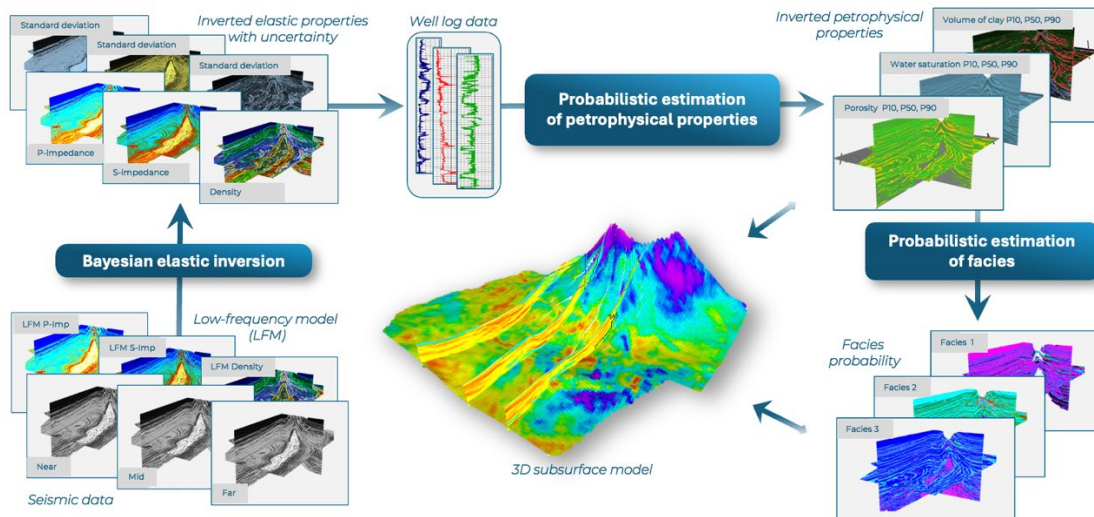


Figure 1: Schematic representation of the seismic reservoir characterization workflow.

Application

The methodology has been applied to a hydrocarbon-bearing clastic reservoir in offshore Angola, in the Lower Congo Basin. The reservoir system consists of a deepwater turbidite system formed within a passive margin and salt tectonics depositional setting, with gravity-driven turbidity currents generating submarine channel-lobe systems. The dominant reservoir facies are medium- to coarse-grained channel-fill and lobe sandstones, characterized by high net-to-gross ratios and good reservoir properties, interbedded with heterogeneous overbank deposits and hemipelagic shales acting as seals. Salt diapirism controls the reservoir architecture as well as mini-basin development, influencing sediment distribution and stratigraphic trapping; this setting results in stacked, laterally variable sand bodies with significant compartmentalization due to structural and stratigraphic complexity. The target interval includes three Middle/Lower Miocene reservoirs, identified based on sedimentological models and unique stratigraphic features, with four lithological facies recognised: high-concentration turbidite (F1), low-concentration turbidite (F2), very low-concentration turbidite and hemipelagic shale (F3), and sandy debrite and traction high-concentration turbidite (F4).

A set of 3 partial-angle seismic stacks and more than 10 wells are available each of them with measured logs, computed petrophysical curves, and interpreted facies profiles. These facies are distinguishable in

both the petrophysical and elastic domains (Figure 2). The available partial stacks are jointly inverted within a Bayesian framework to estimate P-impedance, S-impedance, and density volumes. The wavelets were independently estimated for each angle. The low-frequency models (LFMs) of P-wave velocity was constructed using the E-FWI results (Lo Duca et al., 2026), providing prior models with higher frequency content (up to 20 Hz), accuracy, and correlation with well log data. LFMs of S-wave velocity and density are calculated using linear regressions. The results of the Bayesian AVO inversion include the posterior distributions of elastic properties (Figure 3).

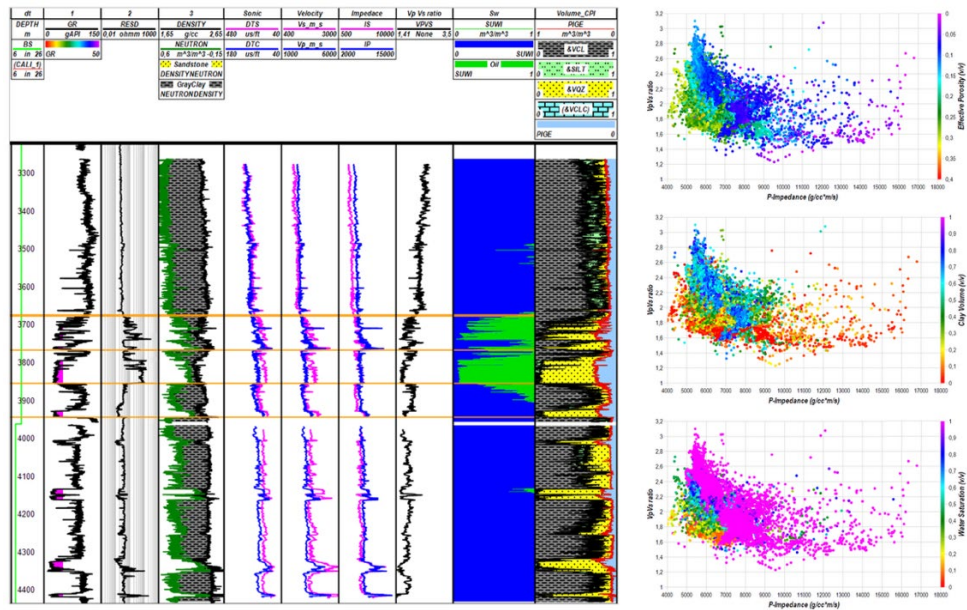


Figure 2: (Left) Well log data from Well 1: from left to right, Gamma ray (GR), deep resistivity (RES), density and neutron porosity, P- and S- wave sonic, P- and S-wave velocity, P- and S-impedance, V_p/V_s ratio, and computed water and oil saturation, effective porosity, and volumes of minerals. (Right) Crossplots of petro-elastic properties: from top to bottom, P-impedance versus V_p/V_s Ratio coloured by effective porosity, volume of clay, water saturation.

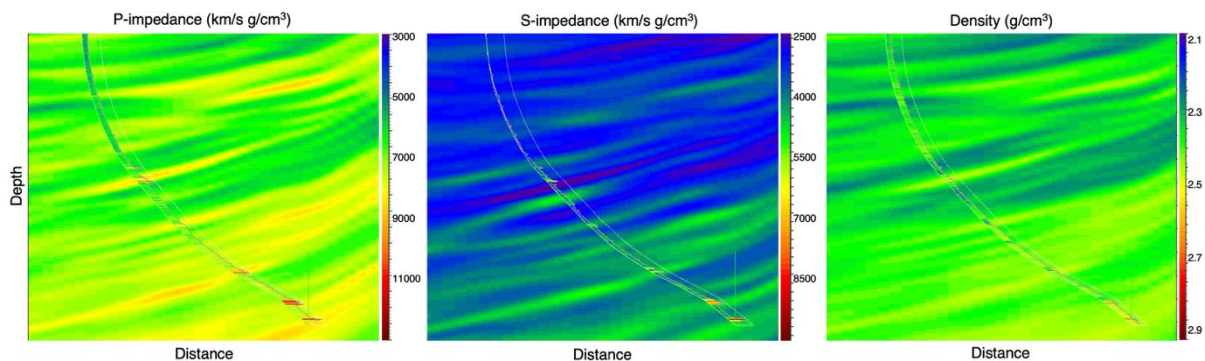


Figure 3: Mean values of inverted elastic properties along a 2D seismic line crossing the borehole: P-Impedance, S-Impedance and density volumes with corresponding well log data.

The prior distribution of petrophysical variables is a four-component Gaussian Mixture, with weights equal to the observed proportions of the four facies in the calibration. The integration of the Bayesian linearized AVO results, the probabilistic upscaling and the statistical rock physics model provide the posterior distribution of effective porosity, volume of clay, and water saturation as well as the posterior probabilities of the four facies across the 3D volume (Figure 4). The inversion also provides the percentiles of the estimated properties to assess the estimation uncertainty.

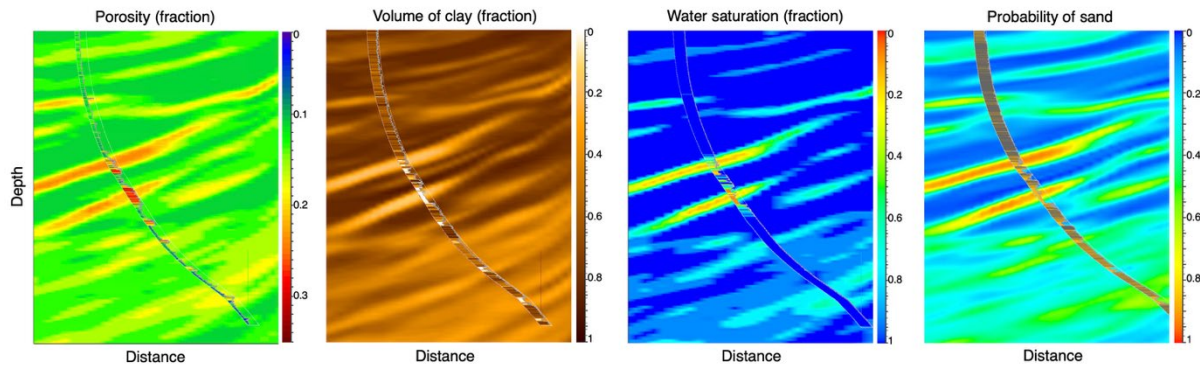


Figure 4 Estimated values of inverted petrophysical and probability of sand facies: from left to right 50th percentile of porosity, volume of clay, water saturation and probability of sand facies (facies F4) with superimposed log data along the well.

Conclusions

This work combined seismic processing, inversion, rock physics modelling, and reservoir characterization. The proposed methodology was applied to a real field characterized by complex geology and challenging imaging due to the salt tectonic, with the aim of strengthening reservoir characterization through the integration of seismic and well log data. The inversion provides an estimated model that accurately matches well log data and quantifies the uncertainty of the predictions. A key advantage of this approach lies in its ability to generate reliable probability volumes of petrophysical properties and reservoir facies through a consistent integration of elastic attributes and petrophysical parameters using E-FWI-informed models and data-drive statistical relations from well logs. These outputs are effectively used for both quantitative seismic interpretation and reservoir modelling.

Acknowledgements

The authors would like to thank Eni Global Natural Resources, Azure Energy and its partners in Block 15/06, SSI, Sonangol and ANPG for permission to show this work

References

- Avseth, P., Mukerji, T. and Mavko, G. [2005]. *Quantitative Seismic Interpretation: Applying Rock Physics Tools to Reduce Interpretation Risk*. Cambridge University Press, Cambridge.
- Eidsvik, J., Avseth, P., Omre, H., Mukerji, T. and Mavko, G. [2004]. Stochastic reservoir characterization using prestack seismic data. *Geophysics*, **69**(4), 978–993.
- Buland, A. and Omre, H. [2003]. Bayesian linearized AVO inversion. *Geophysics*, **68**(1), 185–198.
- Grana, D. and Della Rossa, E. [2010]. Probabilistic petrophysical-properties estimation integrating statistical rock physics with seismic inversion. *Geophysics*, **75**(3), O21–O37.
- Grana, D., Fjeldstad, T. and More, H. [2017]. Bayesian Gaussian mixture linear inversion for geophysical inverse problems. *Mathematical Geosciences*, **49**(4), 493–515.
- Lo Duca, F., Panizzardi, J., Ravasio, A., Bienati, N., Paramo, P. and Lanzarone, P. [2026]. From Elastic FWI to Probabilistic Seismic Inversion for Reservoir Characterization: Integrated Workflow at the Agogo OBN Subsalt Field (Block 15/06, Offshore Angola). SEG/AAPG, Extended Abstracts.
- Mukerji, T., Avseth, P., Mavko, G., Takahashi, I. and González, E.F. [2001]. Statistical rock physics: Combining rock physics, information theory, and geostatistics to reduce uncertainty in seismic reservoir characterization. *The Leading Edge*, **20**(3), 313–319.
- Paparozi, E., Grana, D., Mancini, S. and Tarchiani, C. [2011]. Seismic-driven probabilistic classification of reservoir facies and static reservoir modeling. Extended Abstracts, European Association of Geoscientists & Engineers, cp-238-00352.