Geostatistical Reservoir Characterization in Barracuda Field, Campos Basin: A case study

Frank Cardoso Pereira (CGG)*, Ted Holden (CGG), Mohammed Ibrahim (CGG) and Eduardo Porto (CGG).

Abstract

Deterministic seismic inversion methods have been successfully used in many exploration and production projects. Some of the benefits of these methods are: the inverted impedances are rock properties tightly calibrated with well data; the seismic inversion process reduces the wavelet and tuning effects, and enables quantitative predictions of reservoir properties, all of which are advantages to improving the understanding of the reservoir geology and better planning for the drilling programs. However, when the reservoir is below the resolution of the seismic and/or has thin, low permeability barriers (compartments), estimating the reservoir volume and/or evaluating the connectivity in the reservoir geobodies from deterministic seismic inversion become less accurate and in many cases unfeasible. In such instances, geostatistical (stochastic) seismic inversion method provides more accurate reservoir volumes, and the uncertainties associated with the 3D models can be assessed and quantified. For the work described in this paper, we used a stochastic inversion methodology, which simulates many possible realizations, to better discriminate the thickness and areal extent of the sand/shale layers, and estimate the uncertainties of sand volumes (P10, P50 and P90) in the Oligocene reservoir of the Barracuda Field, Campos Basin, offshore Brazil.

Introduction

Quantitative interpretation of elastic reservoir properties from seismic inversion has become the standard in the petroleum industry and is essential both in prospect mapping during hydrocarbon exploration and in reservoir characterization during appraisal and production. There are several different approaches, including the stochastic versus deterministic methods, which we will show here. The common goal of all these methods is to extract information about lithology (facies), reservoir quality, pore fluids and pore volumes from the seismic amplitudes (Chopra and Castagna, 2014).

In this work, we initially performed a deterministic inversion to understand the main features in the reservoir and to provide quality controls for some of the inputs (wavelets and signal-to-noise (S/N) ratio) to the followed on stochastic inversion to better discriminate the Oligocene reservoir. It's worth mentioning that the inversion results from deterministic were not used as inputs to the stochastic inversion.

The Barracuda Field is comprised of turbidite deposits (sandstone) of Carapebus Formation, from Paleocene to Oligo-Miocene age (which is our target reservoir in this project). The field also includes another carbonate reservoir, the Macabu Formation, (Pre-Salt) of Aptian Age. The field was discovered in April 1989. It covers an area of about 157 Km^2, in water depths ranging between 600 and 1200 m. It produces from Tertiary turbidite reservoirs and from seismic attribute analysis it is feasible to discriminate the oil-saturated Paleocene, Eocene, and Oligocene sandstones encased in shale and marls, mainly in stratigraphic traps (Guimaraes, et al., 2001).

In the deterministic inversion, we produce what we consider to be a single "best" solution. In geostatistical inversion, we produce many possible solutions, all equally plausible. The basic idea is to generate multiple realizations of elastic properties with high-frequency content that are consistent with both seismic amplitude and well data (Doyen, 2007). The geostatistical inversion process is followed by facies classification using the inverted elastic properties along with a Bayesian framework process.

Nowadays, a reservoir characterization workflow requires integration of available data sources across all geoscience disciplines. These different data are often highly dissimilar in resolution (both vertical and horizontal) and in signal-to-noise ratio. They also respond differently to the rock properties. A probabilistic approach, as embodied in geostatistical inversion methods, is a natural route towards quantitative integration.

The dataset available for this work includes: a 220 Km^2 post-stack 3D seismic volume and 3 wells (1RJS 0380, 1RJS 0383 and 6BR 0033) with sonic, density, gamma ray, and resistivity logs. Besides, the well completion and well testing data were available for these wells.

Theory and Methodology

Suitable seismic data conditioning was conducted to enhance the S/N ratio. Proper editing was performed on the log data to eliminate anomalous spikes on the data. Petrophysical analysis was performed to produce logs of the reservoir properties, including porosity, volume of shale, volume of sand, water saturation, and facies. After that, a rock physics model was constructed for: synthetizing logs in sections that have been affected by washout, invasion or missing data; characterizing rocks based on elastic properties and establish the link between petrophysical (reservoir) and elastic properties.

One of the crucial steps in seismic inversion is the wavelet estimation. An appropriate well-tie process was carried out, with the objective to estimate a suitable wavelet with appropriate amplitude and phase for use in the inversion process.

After that, horizon interpretation was performed, based on the interpretation on the well logs and the concepts of seismic stratigraphy, with the main objective to build a geological model, also known as low-frequency model, required as an input for deterministic inversion.

When seismic velocity from the seismic processing is available, it could also be used to control the well log interpolation process between and away from the well locations for the low-frequency model. For this work the seismic velocity was not available.

Deterministic Inversion

For the deterministic inversion, we used a model-based algorithm (Russell & Hampson, 1991) to invert the seismic amplitude (Figure 1A) to an acoustic impedance volume (Figure 1B).

In the model-based deterministic inversion, we start with an initial model of the earth's geology and perturb this model until the derived synthetic seismic section best fits the observed seismic data.

Based on the results from the deterministic inversion, we see some advantages of working with inverted data when compared to working with seismic amplitudes; on the section view, we have a better idea about the spatial reservoir distribution from the inverted data (Figure 1B) rather than the seismic amplitude data (Figure 1A), due to the removal of side-lobes and tuning effects, and the fact that inverted acoustic impedance is tightly calibrated with rock properties. However, the acoustic impedance from deterministic inversion remains in the seismic frequency domain, so we could not distinguish thin facies which are below the seismic resolution.

For this problem, geostatistical inversion was carried out to provide subtle details and quantification of uncertainty (what we will talk about later), as shown in Figure 1C.
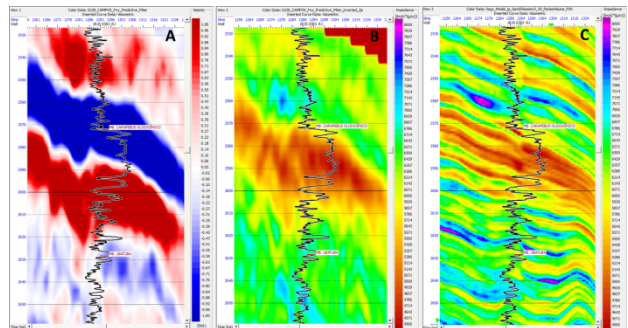

Figure 1 – Inline through the well 1RJS 0383. A) Conventional seismic data, B) Deterministic inversion result, and C) Geostatistical inversion result, with the Volume of Sand log (the Vsand increases to the right).

Geostatistical Inversion

The geostatistical inversion method presented here is described in Escobar, et al., 2006 and Williamson, et al., 2007, which is a combination of Bayesian linearized AVO inversion method (Buland & Omre, 2003) and the widely used Sequential Gaussian Simulation technique (Armstrong, 1998). This methodology provides an efficient means to generate multiple realizations of P-impedance over an area of interest. It works directly in a stratigraphic grid, with vertical sampling less than that of the seismic data, and the process runs in the time domain. Each realization fits available seismic and well data to within user-supplied uncertainties, in addition to a priori impedance mean (as a model), impedance uncertainties and spatial (vertical and lateral) correlations from geostatistics. The realizations are plausible samples of the global posterior distribution of the reservoir and provide the measure of variance of all the input parameters. A schematic representation of the stochastic inversion workflow (Delbecq and Moyen, 2010) is shown in Figure 2.
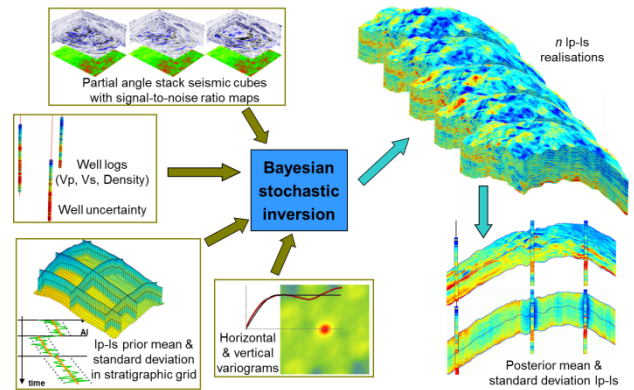

Figure 2 – Schematic stochastic inversion workflow illustrating the required input data, parameterization and outputs. Taken from Delbecq and Moyen (2010).

Bayesian facies classification

A good approach to the stochastic inversion workflow is to derive facies prediction through Bayesian facies classification and volumetric uncertainty (Doyen, 2007 and Moyen & Doyen, 2009), as described in Figure 3. Start with *n* realizations of inverted acoustic impedance. In a cross-plot, we define Probability Density Functions (PDFs) to different facies classes, each point of each realization is classified as sand or shale (in our case) depending on the posterior probability of each facies. Using this procedure, we can generate as many facies models as we have impedance realizations. By counting the number of models classified as sand in each cell, we can compute a sand probability volume. Finally, we can perform a sand volume calculation from each facies model and construct a histogram of the different volumetric estimates. From the sand volume histograms, we can for example determine the realizations that generate the P10, P50 and P90 percentiles. A percentile is a measure used in statistics indicating the value below which a given percentage of observations in a group of

observations fall. For example, the 10th percentile or P10 is the value (or score) below which 10% of the observations may be found.
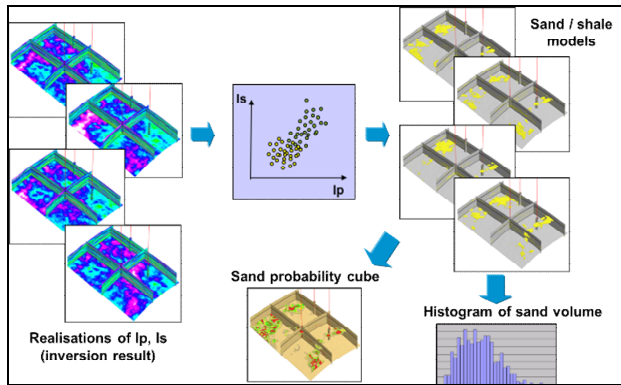

Figure 3 - Bayesian facies classification workflow. Taken from Doyen (2007).

Results

When comparing the deterministic inversion results with the stochastic inversion results, we can see several advantages. Firstly, due to the higher frequency of geostatistical inversion, we see a dramatic improvement in the vertical resolution. This high-frequency information comes from modeling at fine sampling interval, well control, and geostatistical model consisting of histograms and variograms (mainly the vertical variogram). While incorporating the vertical variability information from the wells, the results always honor the input seismic data within a specified variance. Secondly, the separation between the different compartments in this type of reservoir is better defined and can be interpreted from the geostatistical results compared to the less contrast of deterministic results (Figures 1 & 4).

The higher details of the geostatistical inversion can be seen at the well location. In Figure 4, from the left to the right; we have the facies log, sand is yellow and green is shale; the effective porosity log; the water saturation log; seismic amplitude and the synthetic trace in black; the deterministic; and geostatistical inversion with the P-impedance log overlay (at well resolution) from well 1RJS 0383. We observe a better match between the acoustic impedance from the log and the acoustic impedance from the geostatistical results as compared to the deterministic results. Also, we can see the better imaging of the details from a stochastic realization discriminating the permeability barriers (shale) from the net pay (sand) between the Oligocene reservoirs. It is not possible to achieve comparable results with only deterministic inversion in this case.
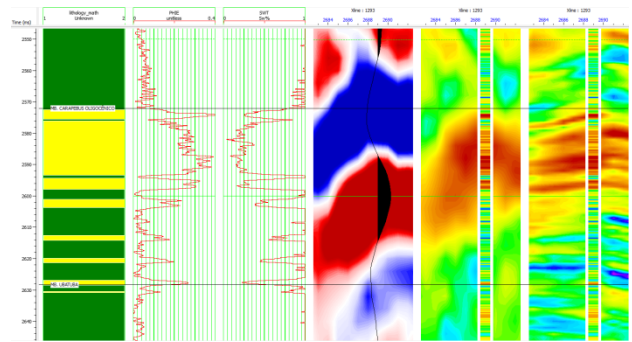

Figure 4 - Composite plot of the well 1RJS 0383 comparing: facies log, effective porosity log, water saturation log, conventional seismic (with synthetic trace), deterministic inversion and geostatistical inversion, from the left to the right tracks respectively, where the increased details from the geostatistical inversion approach can be appreciated. The well log overlaid on the deterministic and geostatistical results is P-impedance log at well resolution.

Given the vast amount of data involved, it is impractical, or even impossible, to interpret each P-impedance realization individually. The meaningful analysis of the realizations is done after facies classification by the computation of the volume of sand geobodies for each realization. This enables the selection of individual realizations, representing for example, P10, P50 and P90 scenarios of sand volumes (Figure 5), to be used for more detailed reservoir modeling. Further analysis could involve the estimation of reservoir properties such as effective porosity from an evaluation of each exported P-impedance realization along with its corresponding sand/shale model. Moreover, by counting in each cell the number of realizations classified into each facies, we could compute a facies probability cube, as shown in Figures 6 & 7, and evaluate the uncertainty in seismic facies prediction.
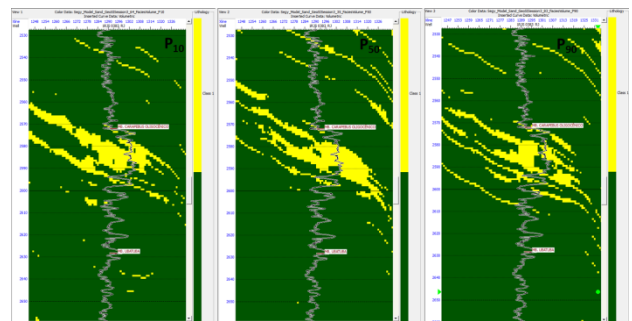

Figure 5 – Section view intersecting well 1RJS 0383 and describing three individual facies realizations generated using the P-impedance and representing the P10, P50 and P90 scenarios, yellow is sand and green is shale. The facies volume was used as the cutoff criterion for ranking. The log curve displayed is the Volume of Sand log (the Vsand increases to the right).
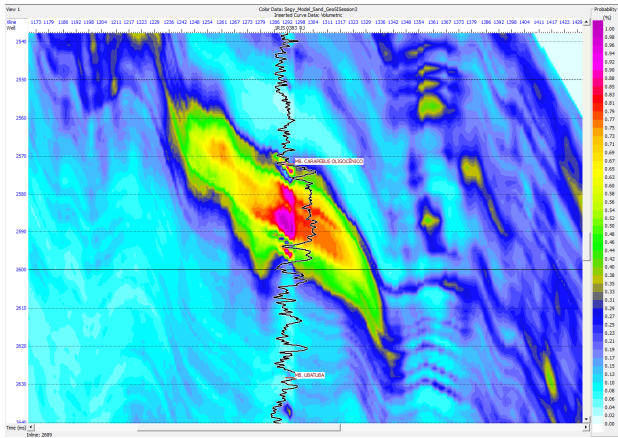
Figure 6 – Inline passing through well 1RJS 0383, showing the vertical and lateral variations in sand probabilities, with the Volume of Sand log (the Vsand increases to the right).
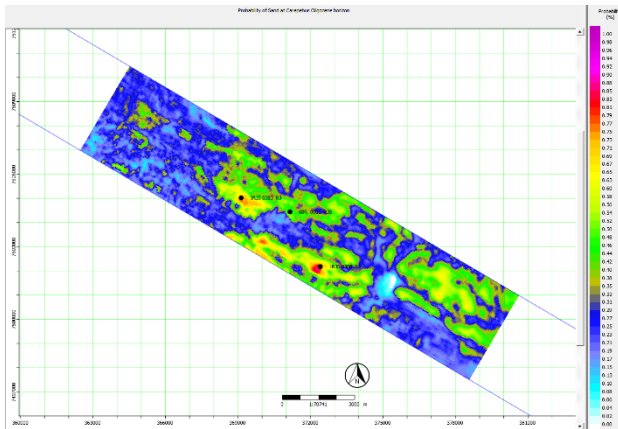

Figure 7 – Horizon slice at the Oligocene reservoir, showing the lateral variation in sand probabilities.

Based on the results of facies classification (Figure 5) and sand probabilities (Figures 6 & 7), we can make some assumptions about the use of these outcomes to enhance the interpretation process. In a qualitative way, the products could improve the knowledge of the reservoir by helping us to better define the architecture and geometry of the target. Additionally, these powerful attributes could be used to support important decisions, such as where we will drill, and guide the geoscientists and/or engineers during the drilling operations. Also, the uncertainty inputs could lead to better risk management and designing the well programs. In quantitative interpretation, having such details from geostatistical inversion would allow better estimation of petrophysical properties, such as estimating sandstone porosity from the P10, P50 and P90 scenarios (Figure 8). Using various realizations in combination with the sand probability volume could improve decision making in the reservoir modeling process to optimize the drilling designs and field development plans.
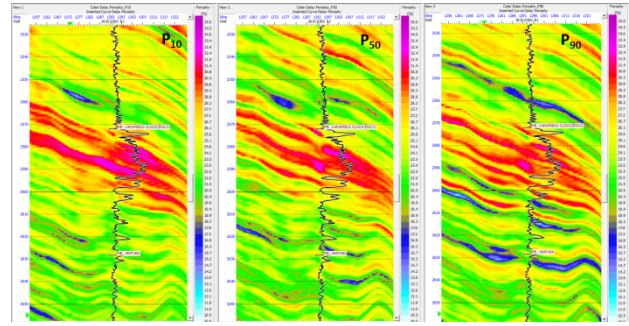

Figure 8 – Section view intersecting well 1RJS 0383 and describing three individual porosity volumes generated using the P-impedance for the P10, P50 and P90 scenarios. The log curve displayed is the effective porosity (the Phie increases to the right).

Conclusions

In this work, we have illustrated the benefits of geostatistical inversion to improve the vertical details, especially when the target is below the seismic resolution and/or has a permeability barrier between the pay, and horizontal continuity through stratigraphic control, of seismic inversion results.

In addition, the geostatistical inversion has the advantage of uncertainty analysis using facies. We computed the facies probability cube for uncertainty analysis and designed realization ranking criteria for P10, P50 and P90 sand volumes for geological scenarios analysis. We saw that this volume analysis could be used to reduce the risk associated with drilling designs and field development plans.

Acknowledgments

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