Joint estimation of reservoir saturation and porosity from seismic inversion using stochastic rock physics simulation and Bayesian inversion.

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Abstract

We used Bayesian inversion and Monte Carlo simulation to jointly estimate porosity and saturation in a deep water channels reservoir interval. Rock physics analysis using fluid substitution provided cut off values for seismic inversion attributes for different amount of water saturation, allowing the directly comparison with estimated saturation from stochastic simulation. The comparison between the two methods showed good agreement in the reservoir interval section for the water saturation estimation, validating the inversion process. Although, further analysis are required in order to validate the estimation results for porosity.

Introduction

Recent advances in seismic inversion techniques (e.g Ma et al., 2002) have improved our ability to estimate reservoir porosity and saturation, leading to better reservoir appraisal. Rock properties like acoustic impedance (Ip), shear impedance (Is) and density extracted from seismic amplitudes are being used with good practice in the daily work by geologist and geophysicist to estimate reservoir porosity and saturation.

Bachrach (2006) developed a method to jointly estimate porosity and saturation using seismic inversion attributes and stochastic rock physics modeling. His method uses Monte Carlo simulation and Bayesian inversion in order to estimate porosity and saturation from rock properties estimated from seismic inversion.

Bachrach (2006) method's to jointly estimate porosity and saturation using seismic inversion attributes is applied here in middle Miocene deep water channels, offshore Angola. The reservoir is comprised of high porous (~ 20%) sandstone, with thickness ranging from 10 m to 20 m.

Seismic inversion attributes were obtained in the area using a simultaneous inversion algorithm based in simulated annealing. The inversion results were quality controlled using available well logs and confirmed as representative of subsurface rock properties.

Fluid substitution analysis using Gassman's equation (Gassman, 1951) was performed in order to investigate the effect of different amount of water saturation in elastic attributes. This analysis allows the estimation of cut off values for different amount of water saturation which can be compared with the results from applying Bachrach (2006) methodology.

Rock physics analysis

Rock physics analysis using available well logs found that Ip and Ip-Is are the main attributes that discriminates oil sands from brine sands. Figure 1 shows a cross plot of Ip x Ip-Is for the only well where it was found oil in the area. Note that using only Ip-Is it is possible to establish a cut off value for different amount of oil sand saturation.

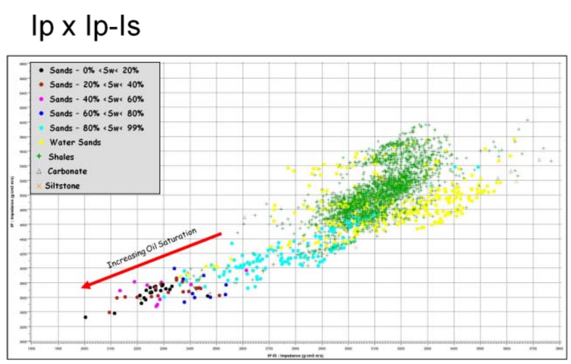

Figure 1: Ip x Ip-Is for the only well where it was found oil in the area. Note that increasing the amount of oil decreases both Ip and Ip-Is. From this figure it is possible to establish a cut off for Ip-Is for different amount of water saturation.

In Figure 2 we cross plot Ip x Ip-Is for all available wells in the area. In this cross plot it is possible to identify 3 main clusters: oil sand, brine sand and shale. Note also the overlap between brine sand and shale. This overlap between brine sand and shale makes difficult to accurately map the brine sand interval using elastic attributes estimated from seismic inversion. Although, the oil sand can be easily mapped using Ip-Is attribute.

Using Gassman's equation (Gassman, 1951), the brine and oil sand interval showed in figure 2 was substituted by different amount of oil saturation. This analysis allowed the establishment of different cut off values for Ip-Is for each amount of water saturation (Figure 3).

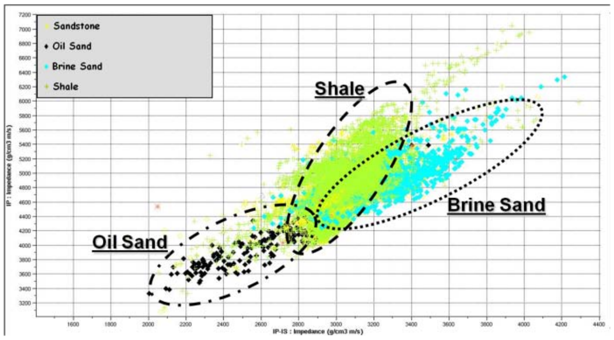

Figure 2: Cross plot of Ip x Ip-Is using available well logs showing three main clusters: brine sand, oil sand and shale.

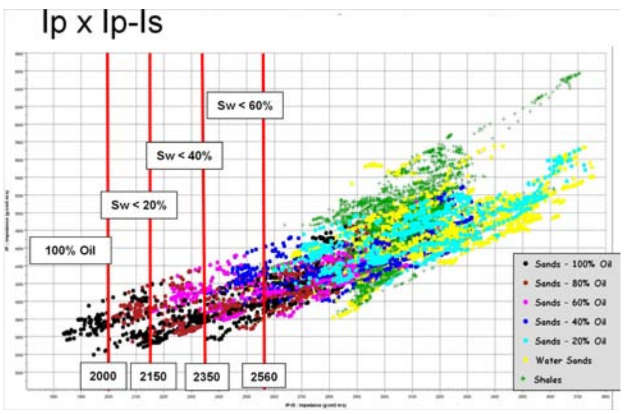

Figure 3: Cross plot of Ip x Ip-Is using available well logs. The brine sand interval and the partial saturated oil interval were fluid substituted by different amount of oil showed in the legend. It is also shown the cut off values for Ip-Is for different amount of water saturation used in the fluid substitution.

Stochastic rock physics modeling

According to Bachrach (2006), sediment porosity and saturation affects bulk modulus, shear modulus and density. Consequently, estimating hydrocarbon saturation and porosity is a joint estimation problem where uncertainty in porosity will lead to errors in saturation prediction, and vice versa.

Within the framework of Bayesian inversion, the following steps are used to estimate the most likely porosity and saturation given a set of seismic attributes

1) Derive a rock physics model for the effect of porosity and saturation on bulk modulus, shear modulus and density for the lithology of interest.

2) Draw random porosity and saturation pairs and derive P-impedance, S-impedance and density.

3) Derive conditional probability density function (PDF) from forward model $P(ATR\,|\,\phi, sw)$

4) Use a lithology indicator to identify specific lithology associated with the rock physics model.

5) Map the seismic-based estimates of Ip, Is and density into the most probable porosity and saturation using the conditional joint PDF estimated in 3, Bayes rule and the maximum-a-posteriori rule.

Bayes rule is give in the equation 1.

$$p(\phi, sw\,|\,ATR) = p(ATR\,|\,\phi, sw) \times \frac{p(\phi, sw)}{p(ATR)} \quad \text{eq. 1}$$

In equation 1, $p(\emptyset, sw|ATR)$ is the posterior joint PDF of porosity and saturation, $p(ATR|\emptyset, sw)$ is the likelihood function obtained from direct rock physics modeling, $p(\emptyset, sw)$ is the prior joint PDF of porosity and saturation and $p(ATR)$ is the probability associated with the expected range of the seismic attributes ATR.

The posterior PDF for porosity and saturation showed in equation 1 spans a range of values. For practical considerations, only one values is taken as representative of this PDF, which is given by the maximum a posteriori (MAP) point estimator. The MAP estimator minimizes the Bayes risk and is given by:

$$(\phi, sw) = \arg\max_{\phi, sw} p(\phi, sw\,|\,ATR) \qquad \text{eq. 2}$$

In stochastic modeling, it is necessary to choose the underlying distribution of the random variables, specifically addressing any dependence among then. This relation can be fully characterized by the joint PDF. In this case, the two fundamentals variables are porosity and saturation. As showed by Bachrach (2005), in some cases, such as low-porosity hard-rock environments, porosity and saturation are often correlated. In soft unconsolidated sands, porosity and saturation may not be correlated as the range of porosities are large, and no geological process dictates correlation between porosity and saturation. These interdependencies are studied through well log analysis in order to choose a meaningful prior.

Figure 4 shows the cross plot of porosity and saturation for the reservoir interval analyzed here. The blue points are the reservoir porosity and saturation, while the red points are the values for porosities and saturations which are going to be simulated. Note that assuming any correlation among porosity and saturation (Figure 4a) reduces the number of porosities and saturations pairs which are going to be tested, while when not assuming any correlation among then increases the number of porosities and saturations simulated (Figure 4b).

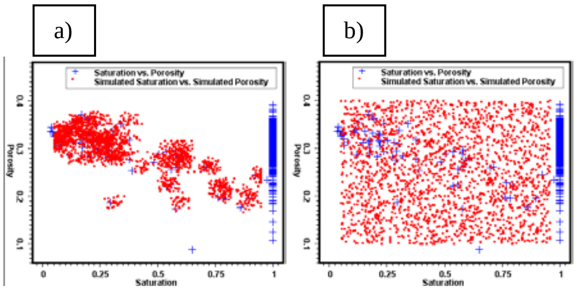

Figure 4: Porosity and saturation cross plot and two approaches for the simulations process: a) assuming that porosity and saturation are correlated b) assuming no correlation among porosity and saturation.

For the reservoir analyzed in this work, we decided not to assume any dependency between porosity and saturation (Figure 4b) in such a way that all range of porosities and saturations are stochastically simulated. For this case, the prior PDF is uniform.

Rock physics model building and stochastic simulations

Using the well log data from a clean sand interval, a rock physics model was derived by fitting a second order polynomial equation to the data. In this approach, it is assumed single mineralogy and basic assumptions like Gassman's equation and Hashin-Shtrickman bounds. Our model also does not assume any specific pore geometry.

Figure 4 shows the cross plot of rock bulk and shear modulus and total porosity (orange dots) for a clean sand (100% quartz) reservoir interval. The blue lines represent a second order polynomial that fits the data and the corresponding standard deviation.

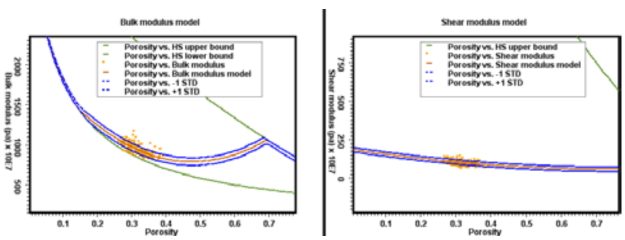

Figure 5: Rock physics model (blue line) estimated using a second order polynomial fit.

Using the rock physics model showed in figure 5, the Monte Carlo method is used to explore all ranges of porosities and saturations and simulate the sediment acoustic response. Figure 6 shows bulk modulus simulated using the rock physics model showed in figure 4b for all range of porosities and saturation.

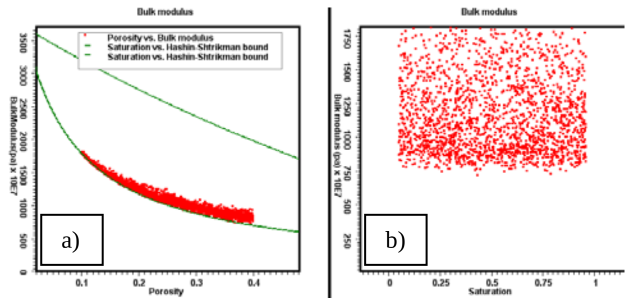

Figure 6: a) Bulk modulus simulated using the rock physics model showed in figure 5 and all range of porosities and saturation from Figure 4b. b) example of 1 milion values of saturation used in the simulation.

We also stochastically simulated density to be able to use acoustic impedance as the main attribute to the joint estimation of porosity and saturation. Figure 7 shows the results of this simulation. Note that from figure 6 and 7 it is extracted the prior probability density function $p(ATR|\phi, sw)$, where ATR in this case is acoustic impedance (Ip).

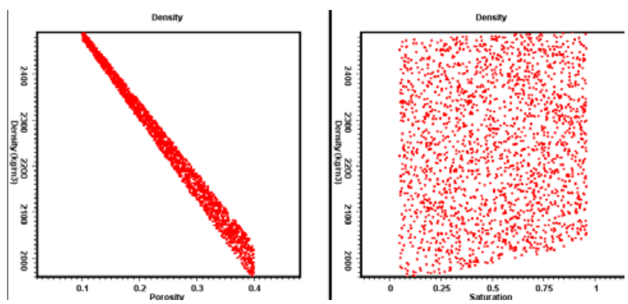

Figure 7: Density simulation using saturation and porosities showed in the figure 1 left.

In this work, the rock physics model showed in figure 4 is not valid for shear velocity, as shown by comparisons between modeled and in situ shear velocity. As a result, we used only Ip information to extract reservoir porosity and saturation.

Posterior Probability density functions

Using equation 1 and the prior PDF built from figures 4, 6 and 7, we are able to apply Bayes inversion for porosity and saturation, obtaining the joint posterior PDF for porosity and saturation.

Figure 8 shows the posterior probability density function assessed for a value of Ip = 3.8e6. The color codes means probability for each porosity and saturation pair. Note that for this value of Ip approximately the maximum probability is found for a porosity value of 0.12 and a saturation of 0.9. The exact value of the maximum probability is found using the the maximum a posterior point estimator (MAP) showed in equation 2.

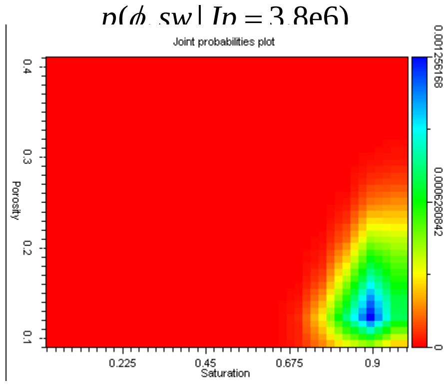

Figure 8: Posterior joint PDF for a value of Ip = 3.8e6. the color bar means probability. The maximum probability is found using the maximum a posteriori point estimator showed in equation 2.

The equation 1 is mapped for each value of acoustic impedance extracted from the simultaneous inversion. As a result, for each values of Ip it will be generated a posterior PDF which maximum probability is found using equation 2.

Using the acoustic impedance derived from seismic inversion and the corresponding prior PDF describe earlier, we are able to map porosities and saturation according to equation 1. Figure 9 and 10 show the inversion results compared with the cut off results derived from fluid substitution showed in the figure 3 for water saturation less than 60 %. The inversion results show good agreement with the fluid substitution results.

The main advantage of the joint porosity and saturation inversion method is the ability to predict true values for saturation and porosity, while cut off values predicts only the limits below or above a certain value of water saturation. One drawback of the establishment of cut off values for different amount of water saturation from fluid substituted logs is the uncertainty in the correct definition of the cut off value, as this depends on the interpreter analysis and can vary from interpreter to interpreter.

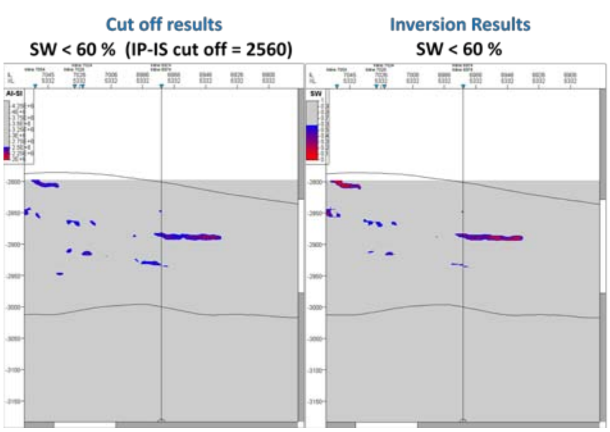

Figure 9: Cross section showing the joint porosity and saturation estimation results (right) compared with fluid substitution results (left) for SW = 60%.

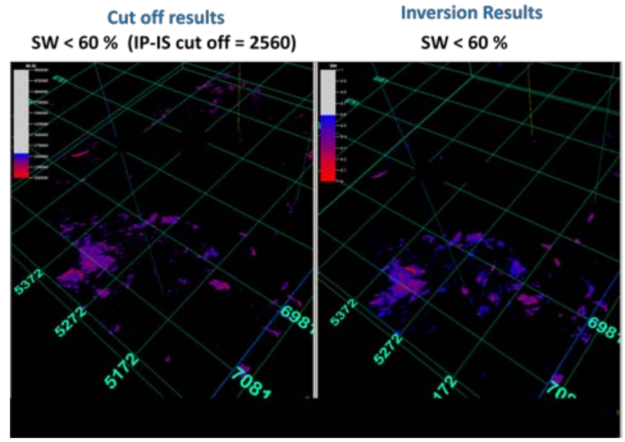

Figure 10: 3D section showing the joint porosity and saturation estimation results (right) compared with fluid substitution results (left) for SW = 60%.

Conclusions

Our results showed that joint estimation of porosity and saturation using Monte Carlo methods and Bayesian inversion provides estimation of water saturation and reservoir porosity based on rock properties derived from seismic inversion. Comparison between the inversion results and cut off values extracted from fluid substitution showed good agreement in the reservoir interval. Further analysis of porosity estimation, which was not shown here, is still required in order to validate the inversion results for porosity.

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