Litho-classification of thin sand reservoirs through Stochastic Inversion and Bayesian Classification: Case study from Syn-rift basin, NE Africa

Havelia Khushboo[1], Mukherjee Anubrati[1], Das Suman[1], Panda Amola[1], Aggarwal Akshay [1], Hazim Sharkhawi[2], Yuxiong Wang[2]*

1. Schlumberger 2. DPOC, South Sudan

KHavelia@slb.com

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Summary

As the reservoirs are becoming complex and thin, far beyond the seismic band width, there is a need to accurately map them and incorporate them into static models. In our study, to build a **Field Development Plan,** in a Meso-Cenozoic rifted basin, the main challenge was to delineate the lateral and vertical continuity between and within thin sand reservoirs. This basin was formed by the formation and development of the Central African Shear zone (CASZ). The obstacle was that the object model approach, based on present day analogue could not explain the hydrodynamic disequilibrium, evident from formation test data (MDT), in the same zone within a single structure. To address this challenge, a robust rock physics model was built using different probability density functions (PDFs) for individual zones, using petrophysical cut-offs and based on Bayesian classification. As seismic data is band limited, most of the thin sand reservoirs could not be individually resolved through seismic inversion and were picked up as packages of thin sands, clubbed along with shales, in the acoustic impedance volume. These predictions were limited to the resolution of the seismic data. Hence stochastic or geostatistical inversion was carried out using the well data and the deterministic acoustic impedance volume as a constraint. The PDFs, from rock physics model, were applied to the stochastic inversion results (stochastic acoustic impedance volumes), to build sand probability models for each reservoir zone. The final facies model, created using stochastic inversion, could effectively explain the sub-compartmentalization of the reservoir zones, consistent with the formation test data and give a better history match. The multiple equiprobable acoustic impedance outputs and sand probability volumes, from stochastic inversion, were used for the uncertainty analysis of the facies model. In absence of pre-stack seismic data and shear logs, this approach can be effectively used to characterize a similar setting elsewhere.

Introduction

The study, performed in a Syn-rift basin of NE Africa, presented the challenge of thin reservoirs with inconsistent production. There was variable production from the 11 wells in the area, from different zones. The fault interpretation could not explain the sub-compartmentalization of reservoir within the individual fault segments (Figure 1).

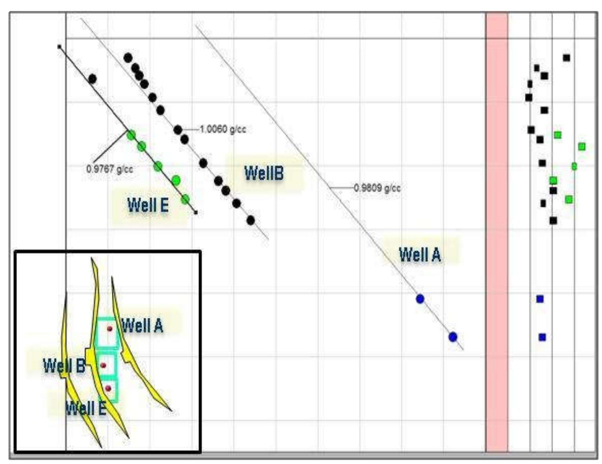


Figure 1a. (inset) Fault interpretation indicates Well A, Well B and Well E are drilled in same fault block, hence should be in hydro dynamic equilibrium.

1b. The MDT result from a particular reservoir level reveals different pressure trends, indicating that the same reservoirs are not in communication in the three wells.

This indicates the importance of capturing the spatial distribution of thin sand which control the fluid dynamics in the area. The use of post-track attributes (Figure 7a) was not successful in delineation of thin sand bodies and their connection. In absence of pre-stack seismic data, a rigorous QI approach on the PSTM stack was needed to explain the reservoir continuity and delineation of sands in these intervals. The challenges were broken down into a logical sequence of interdependent steps starting with the available seismic data and using a detailed well driven approach. The next step was to build a reliable and accurate rock physics model to predict the missing log data and delineate sand bodies based on acoustic impedance logs, by building probability density functions (PDFs). Simple cut-off based analysis was not enough to capture the lithology change. Then the re-processed high resolution seismic was used to run deterministic and stochastic inversion with the former being used as a soft constraint to control the later. Inversion at two different resolutions was carried out to reduce the uncertainty associated with sub seismic geostatistical predictions and to capture the thin reservoirs. The blind well tests for the stochastic inversion result show excellent correlation in existing wells.

Theory and Method

The steps followed are given below in figure 2:

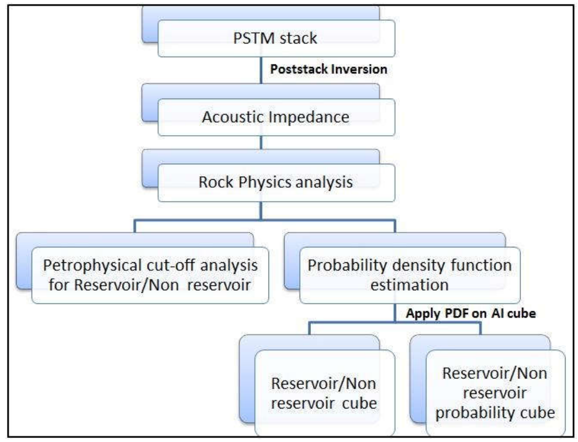
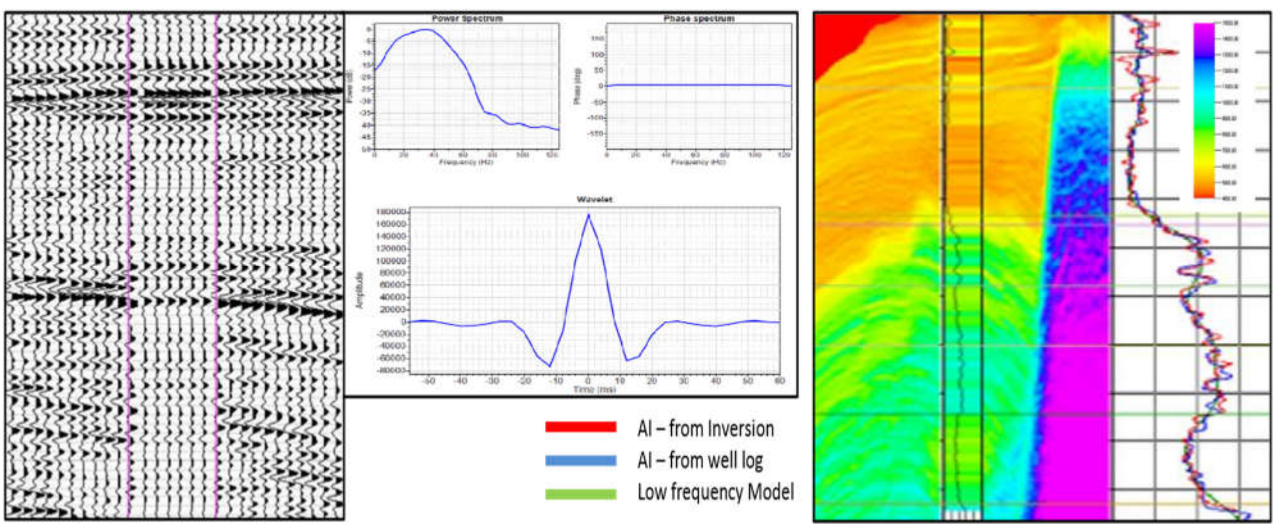


Figure 2: The workflow followed to build a litho-cube in this study.

Seismic Well Tie

Seismic Well Tie was performed for all 11 wells and wavelets were extracted. (Figure 3a, 3b)



(a) (b) (c)

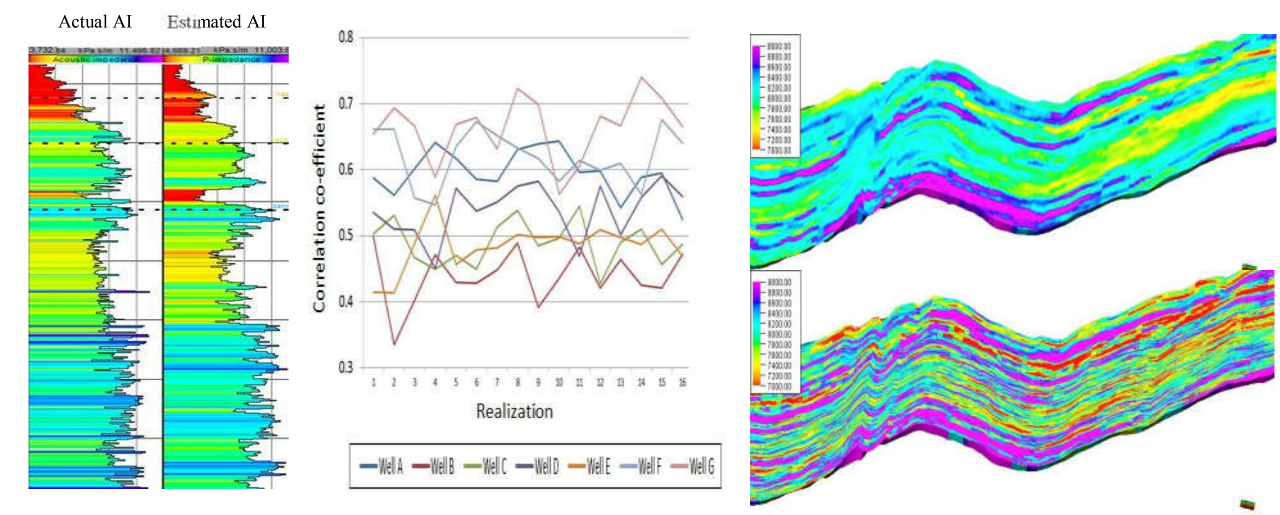
Figure 3(a) Seismic well tie of Well A. 3(b) Wavelet extracted from Well A. 3(c) Simultaneous Inversion match at Well A.

Deterministic Seismic Inversion

Simulated Annealing based global optimization technique was used for obtaining Acoustic Impedance from PSTM stack data. 11 wells were used to generate the Low Frequency Model (LFM). The low frequency model (filtered at 8 Hz) was guided by relative acoustic impedance cube and seismic velocity, to improve the reliability of interpolation between and extrapolation away from the wells. Inversion result match for Well 1 can be seen in Figure 3c.

Stochastic Seismic Inversion

As the sands present in the area were quite thin, a high resolution stochastic inversion approach was required to effectively characterize them. The results from the deterministic inversion were used as a guide for stochastic inversion. Stochastic inversion runs on a geo-cellular model and uses the high frequency logs, trend model and variogram parameters to generate multiple realizations that have the equal probability of occurrence. The stochastic acoustic impedance generated from this, is validated against the seismic cube, based on the level of convergence specified. For our study area, the model was divided into 7 zones, with the vertical resolution of 1 ms each and geostatistical analysis was done separately for each of them. The major-minor range was calculated from the deterministic acoustic impedance whereas the vertical range was taken from the well logs. 16 realizations were run with a high convergence value. These realizations were ranked based on blind well tests done on 7 wells. The correlation between the estimated and actual acoustic impedance was calculated and a plot was made to choose the best 5 realizations, which were then averaged out to smoothen the extreme values (Figure 4a and 4b).



(a) (b) (c)

Figure 4 Stochastic Inversion results (a) Blind well test at Well A. 4(b) Blind well test correlation matrix run for 7 wells and 16 realizations. 4(c) Comparison between the resolution of deterministic AI(top) and stochastic AI(bottom) for one section. Red, yellow and green colors are highlighting the sand packages.

Sand Probability estimation

A good correlation was observed between occurrences of sand bodies and low acoustic impedance values in most of the intervals of the study area. But sand was not delineated using simple acoustic impedance cut-offs. Instead sand and shale was separated using probability density functions, which are more precise.

Facies log, at well level, were built using the below petrophysical cut-offs. Sand was defined as:

- Volume of shale < 0.45
- Effective Porosity > 0.12

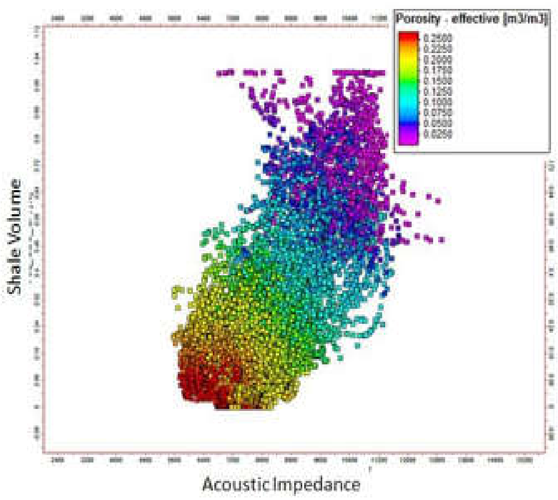


Figure 5 Rock Physics Analysis - Vshale vs Acoustic Impedance plot for Zone 2, colored by Effective Porosity values, showing a good relation between the well logs.

The facies histograms in figure 6 show distinct separation of sand and shale in terms of acoustic impedance values in some zones. In zones with separation, these histograms were used to build the probability density functions (PDFs) for sand, which specify the chance of occurrence of sand at a particular acoustic impedance value. This approach was based on Bayesian classification. As the zones were quite different in sand quality and content, separate PDFs were made for each zone. They were used to convert the final high resolution acoustic impedance cube, form stochastic inversion, into a sand probability cube.

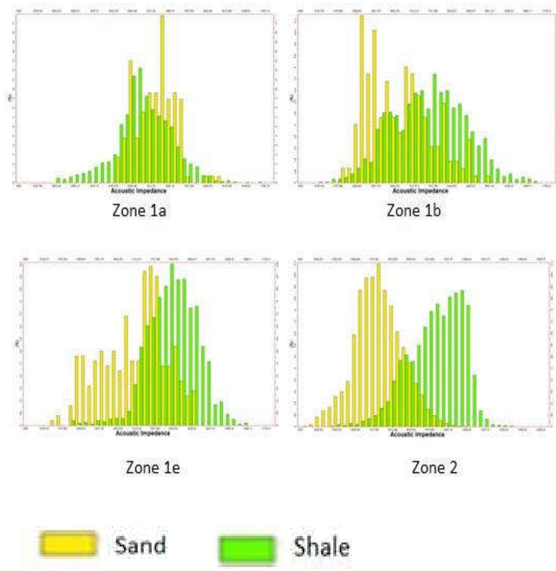


Figure 6 Rock Physics Analysis - Acoustic Impedance histograms for 4 zones, showing the sand shale delineation in some of them.

Facies propagation in the Static model

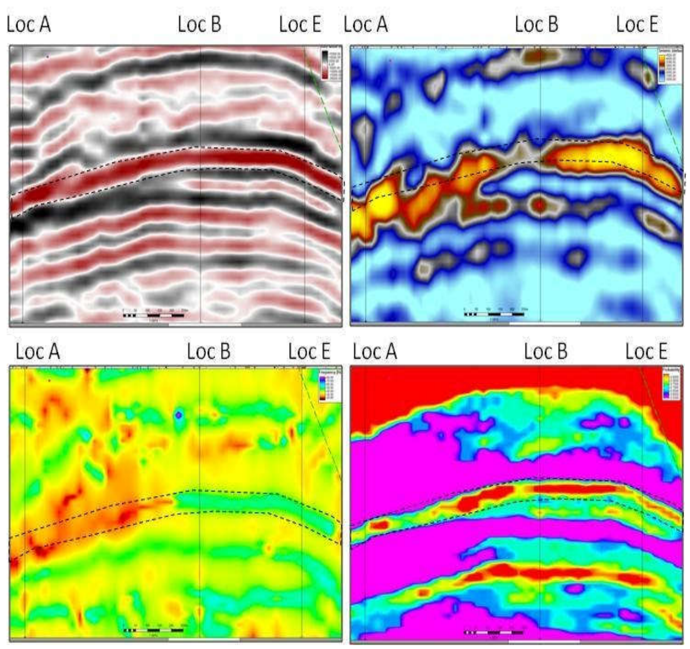
The combined sand probability cube was depth converted and sampled into the static geo-cellular model. It was further refined using the facies well logs and trend modeling. Through this sand probability cube was re-populated in the grid, using the logs as hard data and the high-resolution sand probability cube from stochastic inversion as a guide. This removed and corrected the uncertainty that might have been added during the depth conversion process and sampling of volume into the grid. This also ensures that the sand probability is accurate at the known well locations, making it 1 where the well logs show sand and 0 where they have shale. Multiple probability cut-offs were tested and a cut-off of 0.5 was used to convert the sand probability cube into sand and shale facies property in the static model (Figure 8). Hence the result from stochastic inversion and rock physics analysis was successful in further subdivision of each fault segment, making it consistent with reservoir engineering data. Uncertainty analysis was also run on the applied probability cut-off, to quantify its impact on the hydrocarbon volume in place.

Results

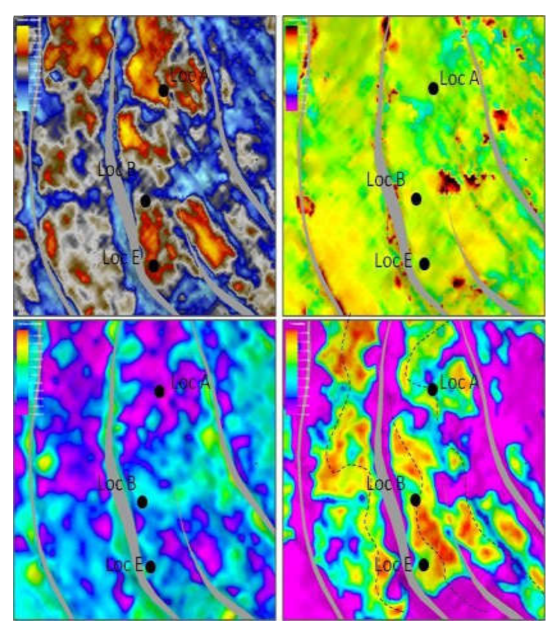
In the present study, stochastic inversion and the use of zone specific PDFs for each reservoir zone (based on Bayesian classification), significantly improved the delineation of thin sand geometry as evident in Figure 7b, which was not possible using post stack attributes. Further the result was able to capture the non-connectivity of reservoirs between the wells making it consistent with the formation test data (MDT) from the reservoir zones (Figure 1a and 1b). This work also indicates that the seismic inversion guided facies modeling approach is a better approximation in reservoir delineation, explaining the fluid dynamics in the area, resulting in a better history match at wells, as shown in Figure 8 for well B.

Conclusions

The study area in syn-rift basin of north-east Africa presented the challenge of characterizing and mapping thin sands. A combination of deterministic and stochastic inversion was used to generate acoustic impedance at different resolutions, with the deterministic acoustic impedance guiding the stochastic results. A robust rock physics model was built for this field and was tested and validated against blind wells. Bayesian classification was used to build the sand probability cubes from the stochastic acoustic impedance, which was input for facies modeling in the static model. It helped in compartmentalization of reservoirs within individual fault controlled segments, justifying the formation pressure data and improving the history match at wells. This devised approach can be followed in similar environments, lacking pre-stack data and shear logs. It will be successful in delineation of thin sand reservoirs, beyond seismic resolution, which are otherwise not easy to pick in deterministic inversion.

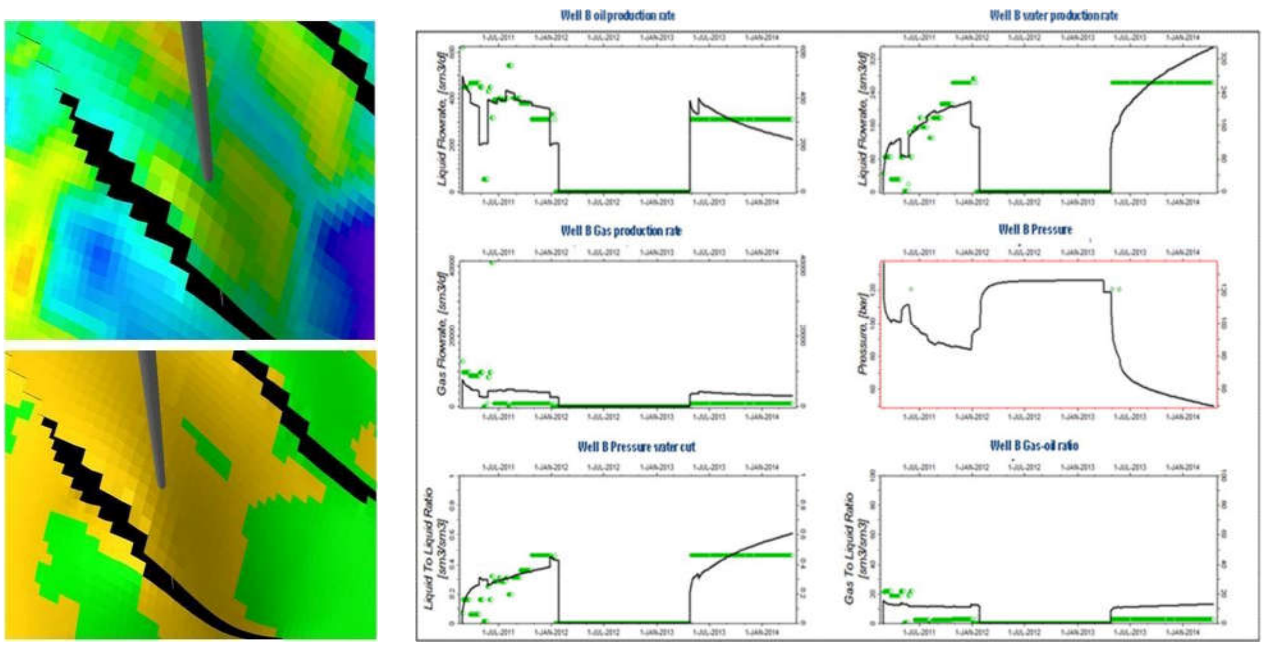


(a)



(b)

Figure 7a. Composite line connecting 3 wells (loc A, locB and loc E, location same as next figure) in PSTM seismic, sweetness, dominant frequency and sand probability volume. The sand probability cube clearly shows the reservoirs are not connected in three wells which is otherwise not observed from post track seismic attributes. Figure 7b Attribute extracted along one of the reservoir (shown in dotted line) in sweetness, dominant frequency, relative acoustic impedance and sand probability volume (location same as previous figure). The channel geometry and non-connectivity of reservoir in 3 locations are clear in sand probability cube.



(a) (b)

Figure 8a. Conversion of sand probability cube into facies in static model (yellow represent reservoir and green represent non reservoir facies). 8b. History match for Well B showing good match.

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