Improving Accuracy on Facies Characterization through Seismic and Log Driven Workflow for Proportion Cubes Generation

Gerardo González (Paradigm), Natalia Goes (Paradigm) and Eliany Terán (Paradigm)

Abstract

Produce an accurate reservoir facies model by the integration of all available data such as seismic, reservoir grid, wells and core data is an important point for a better understanding of reservoir rock behavior.

The methodology described in this paper attempts to perform a multi-disciplinary reservoir characterization workflow, combining seismic facies and electrofacies to build a reservoir facies model able to represent both: the high vertical resolution of well logs and the regional distribution of seismic response.

First, in order to obtain a calibration of the facies at well location, an electrofacies model is created based on rock type characterization using core data, well logs and geological information. The facies groups are defined using MRGC clustering method (Multi Resolution Graph-based Clustering) on the key wells. Subsequently, they are propagated to all the wells in the area.

Second, seismic volumes is analyzed, seismic attributes volumes are computed and incorporated to run a seismic facies classification in a multi-attribute approach.

Finally, once seismic and log facies are created, they are calibrated and integrated to create 3D proportion cubes. These cubes are used as an input to run multiple facies simulation in the reservoir grid in order to produce accurate reservoir facies models.

Introduction

Valid representations of geologic heterogeneity are fundamental inputs for quantitative models building, These models are used to manage subsurface activities, where the simulation of realistic facies distributions represents a critical step (Falivene et al, 2009).

One of big challenges in the geoscience studies is to find a method for integration of different scale data. Wellbore information always represents our hard data, we can take advantage of its vertical high-resolution to understand the electrofacies setting and identify zones by geological interpretation. On the other hand, seismic information is our lateral higher resolution data source; we can extract and combine several kinds of attributes in order to characterize our reservoirs.

This paper presents a methodology to integrate discrete properties interpreted in wells and seismic facies generated through a multi-attribute approach. Initially, we cannot talk about a direct seismic facies and electrofacies correspondence because resolution scales, but we can construct a correlation matrix and study the electrofacies occurrence by each sismofacies. Based on this correlation a facies probability property can be estimated and used as a constraint during facies modelling.

Method

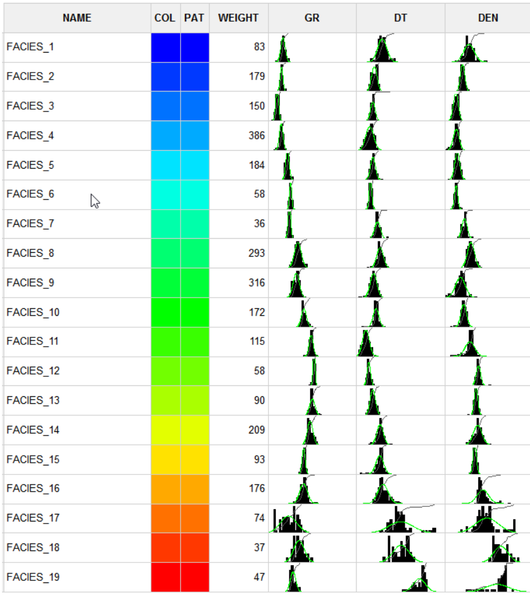
Electrofacies definition

Electrofacies are defined with a methodology based on rock type characterization using core samples, well logs and geological data. In order to obtain a calibration of facies at well location, a well log analysis is performed, starting with the QC process, normalization and finally the petrophysical interpretation.

The main objective of the methodology is to get geology out of logs; considering the main property we need to differentiate lithology and porosity, we select the appropriate combination of logs that represented the geodiversity of the interval, honoring the vertical resolution of rock properties and honoring bed boundaries.

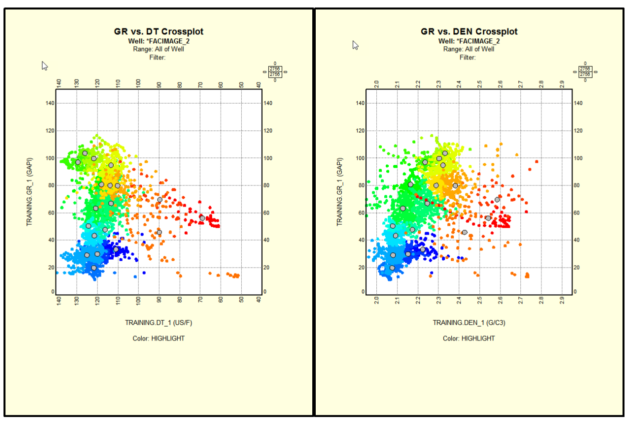
To build the model 1D logs: GR, DT, and RHOB are used. For our example, five wells were selected as reference wells; those wells that have the richest geological information and facies representative for the analyzed interval, the most comprehensive suite of logs and core data for cross validation of results.

All available well data is integrated to sort out log response by similarity to form few groups of electrofacies, these groups share common features that can describe geological formation. The groups are defined using MRGC clustering model (Multi Resolution Graph-based Clustering) for the key wells, electrofacies are correlated with petrophysical properties such as porosity and permeability and core information (Figure 1A). Once the model is calibrated, the geological and petrophysical interpretation is included to label each facies through crossplots and histograms of log responses (Figure 1B) and facies index with depth.



NAME	COL	PAT	WEIGHT	GR	DT	DEN
FACIES_1			83			
FACIES_2			179			
FACIES_3			150			
FACIES_4			386			
FACIES_5			184			
FACIES_6			58			
FACIES_7			36			
FACIES_8			293			
FACIES_9			316			
FACIES_10			172			
FACIES_11			115			
FACIES_12			58			
FACIES_13			90			
FACIES_14			209			
FACIES_15			93			
FACIES_16			176			
FACIES_17			74			
FACIES_18			37			
FACIES_19			47			

A) Multi-Resolution Graphic Clustering Model for 19 ordered facies

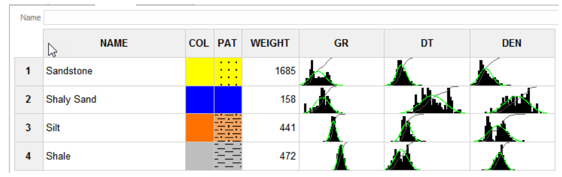


B) Xplot GR vs. DT and GR vs. DEN to show the relationship between log response and cluster

Figure 1 – One model from the 5 clustering models obtained from Multi-Resolution Graphic Clustering method with 19 facies separated and ordered based on log response.

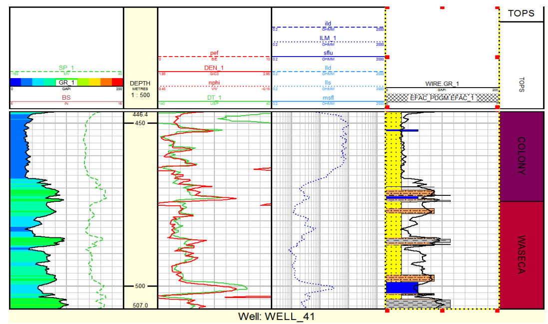
The final step is to propagate the model to all the wells in the area. We perform a similarity analysis before propagating to identify which wells are similar to the reference wells and which are not.

As a result, electrofacies were defined for 5 reference wells and then propagated for all wells located in the area, using 3 logs to train the algorithm: GR, DT, and RHOB. A model of four electrofacies were determined and classified based on log response and petrophysical properties from more shaly formation to clean sandstone intervals (Figure 2A, 2B).



	NAME	COL	PAT	WEIGHT	GR	DT	DEN
1	Sandstone			1685			
2	Shaly Sand			158			
3	Silt			441			
4	Shale			472			

A) Final electrofacies model for 4 ordered facies



B) Electrofacies propagated on reference wells

Figure 2 – Final electrofacies model propagated in the area; electrofacies from original model of 19 facies were combined and labeled from sandy intervals to shaly intervals. The facies index is visualized with depth on layout altogether with other log information and petrophysical properties.

<u>Seismic facies generation</u>

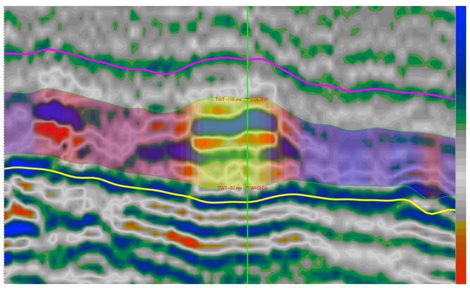
The goal of the multi-attributes classification process is to describe the variability of seismic response, within an interval of interest, in order to reveal details of the reservoir geological characteristics. Low and high vertical variability attributes are selected to characterize the reservoir. Seismic inversion products, complex trace, spectral decomposition and unconventional geometric attributes are combined in this approach to delimit geobodies, determine the structural complexity, reservoir quality and anisotropy directions.
Two different methods for seismic facies volumetric classification are proposed in this work: Hierarchical classification in an unsupervised approach, and by cross plotting attributes in order to classify seismic anomalies (quantitative seismic interpretation).

Hierarchical facies classification is based on multi-dimensional cross-plots and consists of two steps:

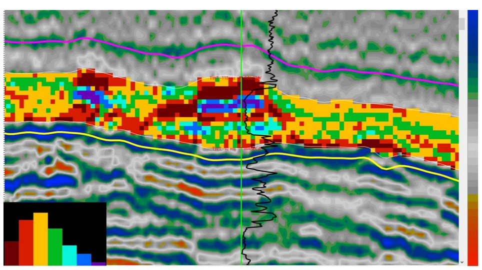
- Characterizing meaningful population subsets and defining a representative “cluster” for each of them.
- Assigning individual samples to the appropriate subset based on the Euclidean distance. Each subset is assigned a color and a number.

The classification produces a single 3-D seismic facies classification volume as output. Each sample of this volume is assigned a seismic facies class number and a color. If two samples have the same class number, they are characterized by similar values in all input seismic attributes and, therefore, they likely correspond to a similar geological environment.

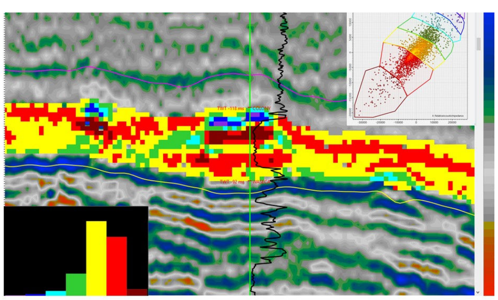
A combination of seismic attributes and the subsequent data reduction (Principal Component Analysis) are used to apply for seismic pattern recognition, generating seismic facies cubes. The Figure 3 shows the interval of interest and two examples of volumetric classification. Several scenarios result from the different combinations of seismic attributes, we can think, for instance, in merging rock properties attributes to characterize reservoir quality with structural attributes to understand compartmentalization, crossplot elastic attributes to delimit anomalies or use other seismic classification algorithms as neural networks to comprehend stratigraphy.



A) Interval of interest. The goal for this example is to characterize a seismic anomaly interpreted as a channel.



B) Seismic classification hybrid method with PCA. Seismic attributes: Hilbert Transform, Colored Inversion, Acoustic Inversion and Relative Acoustic Impedance.



C) Seismic classification using the cross plot between Relative Acoustic Impedance and Hilbert Transform

Figure 3 - Seismic volumetric classification examples with two different approaches for same interval (A): Non-supervised hybrid method (B) and supervised crossplot approach (C). The black curve represent the gamma ray values. The facies matching with low GR values on the well is interpreted as the target channel.

<u>Data analysis, calibration table and 3D proportions</u>

Once the electrofacies are defined for the wells and the seismic facies cube are generated (figure 4), the next step is to analyze both data together. This is performed through calibration of seismic facies to the well facies at the well location to create a 3D proportion cube.

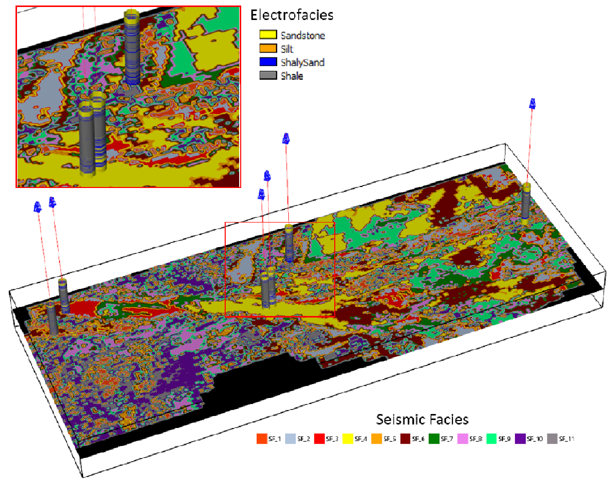


Figure 4 - Seismic facies and electrofacies ready for calibration

The method proposed counts all the collocated well samples for a given seismic facies (SMi) and reports it as a number of samples. All the collocated well samples of each lithotrofacies (EFi) are also counted. Finally, the table (Figure 5) shows the rate of EFi by number of samples, which represents the probability of the EFi electrofacies for a given SMi seismic facies.

The calibration table is used to initialize the facies probability as a property everywhere in the cube where the seismic facies is defined based on the probability computed at the well location, creating a 3D proportion cube.

The final stage of this step is the transference of the facies probability property from 3D proportion cube to modeling grid. This probability property generated can be used during facies modelling.

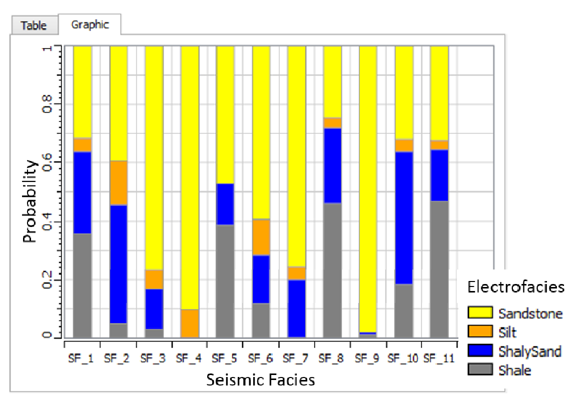


Figure 5 - Calibration of seismic facies vs. electrofacies

Results

Facies distribution

The final step of the workflow proposed is the facies modelling. There are many approaches to perform facies modelling, but the discussion about what is the best one is not the focus of this technical paper. The focus here is to propose the use of probability property created as a constraint to facies modelling.

The method selected for facies modelling in this case was a truncated Gaussian simulation. The hard data was the electrofacies from wells and the proportion constraint was the probability property defined at previous step.

As a result, all simulated facies models preserve the well information and follow the trends from probabilities calculated based on seismic facies for each electrofacies in the 3D proportion cube as shown in Figures 6 and 7.

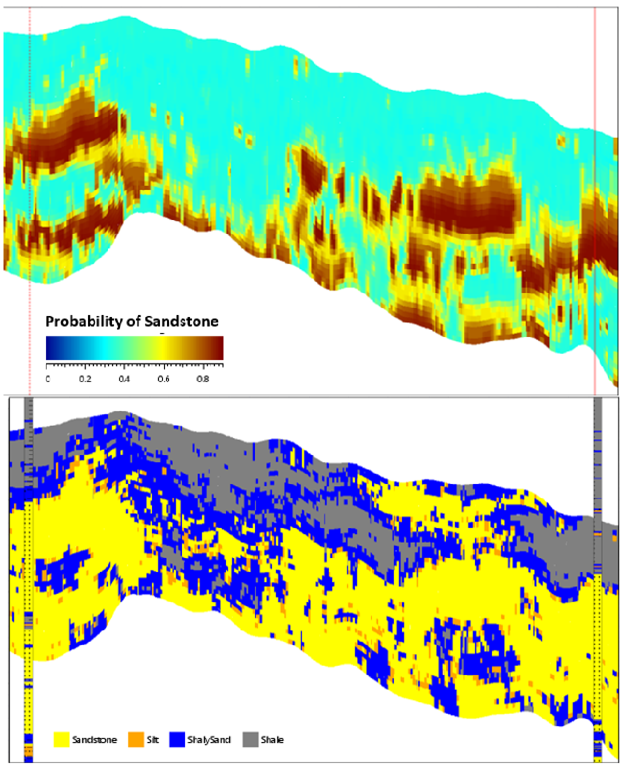


Figure 6 - Cross Section comparing probability of sandstone and one facies simulation

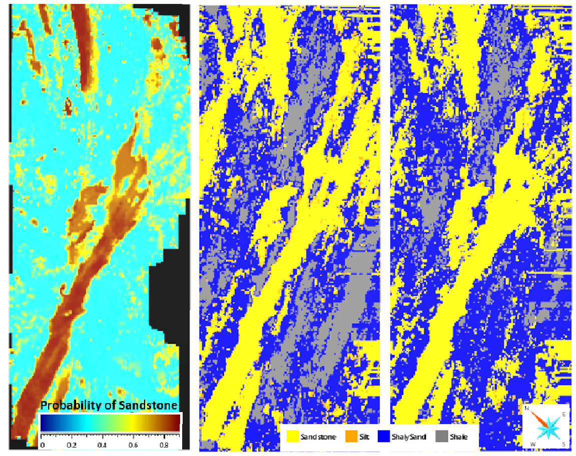


Figure 7 - Map comparing probability of sandstone and two different facies simulation. Notice that the main trend and proportions for sandstone are represented in both results

Conclusions

The possibility to generate several discrete scenarios through combinations of seismic attributes, and validate the quality of classification against wells, makes this methodology proper to improve the geophysical contribution for the geological model building.

3D electrofacies proportion cubes from seismic and wellbore data integration as part of the facies simulation process, represent a constraint that evidently gave a differential for this specific dataset. This method also give the ability to perform uncertainty analysis to evaluate risk and economical potential

Acknowledgments

The authors thank Paradigm for permission to publish and present this work

References

Falivene, O. et al, 2009, A geostatistical algorithm to reproduce lateral gradual facies transitions: Description and implementation. Elsevier

Marroquín, I. D., 2014, A knowledge-integration framework for interpreting seismic facies: Intepretation, 2, SA1 – SA9.

Rabiller, P. 2014, A geology compliant method for Core and Log Integration.

Rabiller, P. 2007, Facies prediction and data modeling for reservoir characterization

Tomaso, K. et al, 2013, Seismic fracture characterization workflow and support for the geological model: Albian carbonate reservoir, Campos Basin, Brazil. Thirteenth International Congress of the Brazilian Geophysical Society