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VACA MUERTA FACIES MODELING IN LOMA CAMPANA - PART 2: 3D SEISMIC IMPEDANCE FOR RESERVOIR PREDICTION

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RESUMEN

Modelado de facies de Vaca Muerta en Loma Campana – Parte 2: Impedancia Sísmica 3D para Predicción del Rerservorio

El modelado de yacimientos convencionales ha sido una práctica estándar de caracterización de reservorios durante décadas, comúnmente utilizada para reducir la incertidumbre del reservorio y estimar la volumetría. Sin embargo, hay pocos ejemplos de caracterización de reservorios tipo *shale* no convencionales desde una perspectiva de flujos de trabajo de modelado, ya que la mayoría de los *plays* de *shale* en todo el mundo solo tienen unos pocos años de historia de producción. Debido a su gran espesor (> 300m), los datos sísmicos de la Fm. Vaca Muerta difieren de la mayoría de los shales no convencionales, ya que pueden resolver la arquitectura estratigráfica interna y los patrones de apilamiento con detalles notables. Además, los datos de la impedancia acústica sísmica invertida han demostrado ser una buena herramienta para predecir tipos de rocas tanto a nivel areal como vertical.

Basándose en la interpretación sísmica 3D, registros de pozos de más de 150 pozos verticales y datos de corona de 3 pozos, se construyó un marco estructural y estratigráfico para la sección progradante de la Fm. Vaca Muerta (*toesets* y *foresets*) en el área de Loma Campana, probando tanto el modelado basado en volumen (VBM) como las técnicas de *pillar gridding* para el modelado estructural. Como parte del proceso de modelado de facies, se definieron 8 electrofacies basadas en perfiles eléctricos básicos, que se correlacionaron exitosamente con datos de impedancia sísmica 3D. Los bajos valores de la impedancia acústica (AI) son representativos de las asociaciones de facies en la Fm. Vaca Muerta con alto contenido de COT y porosidad, mientras que la alta impedancia acústica se correlaciona con las facies calcáreas con baja porosidad de la Fm. Quintuco. Como resultado, 8 facies sísmicas de impedancia acústica fueron generadas y se vincularon a propiedades de rocas discretas, que se utilizaron para propagar facies en el modelo 3D. Aunque los coeficientes de correlación son bajos cerca de la base, aumentan hacia los *toesets* y *foresets* de la clinoforma de la Fm. Vaca Muerta (sección progradante) debido a un mayor contraste de impedancia acústica. La integración de múltiples escalas de datos permitió construir un modelo estático robusto, con un fuerte control de facies basado en electrofacies de pozos y datos de impedancia acústica sísmica 3D. Específicamente, se pudo modelar la distribución de tipos de roca a lo largo del bloque y distinguir entre progradaciones regresivas ricas en carbonato y progradaciones transgresivas con alto contenido de materia orgánica, lo que permite ser más predictivos a la hora de evaluar e identificar posibles *landing points* de pozos horizontales en el área de Loma Campana.

INTRODUCTION

Loma Campana block (Central Neuquén Basin) has been the first unconventional shale resource development project in Argentina, initiated by YPF in 2012 and later joined by Chevron in 2013. The project began with vertical-well development drilling in 2012, followed by horizontal-well drilling in 2015. To-date, Loma Campana is the most data-rich Vaca Muerta Fm. exploitation concession block in the basin, with more than 560 producing wells (430 vertical & 130 horizontal) and 3D seismic coverage in ~95% of the area (Licitra *et al.*, 2016; Vittore *et al.*, 2017). About 150 vertical wells have good set of logs (GR, DT, Res, RHOB, etc), appropriate for well correlation and stratigraphic framework building and 74 of them were used for electrofacies generation (Crousse *et al.* 2018, this congress). In addition, we have used 3D seismic derived products as seismic acoustic impedance inversion and seismic attributes to predict facies away from well control.

Loma Campana'sstratigraphic, structural, sedimentological and well production performance characterization (Licitra *et al.*, 2015; Vittore *et al.*, 2014, 2016; Reijenstein *et al.*, 2017a; 2017b; Rimedio *et al.*, 2015) helped progressour understanding of the block based on existing well and

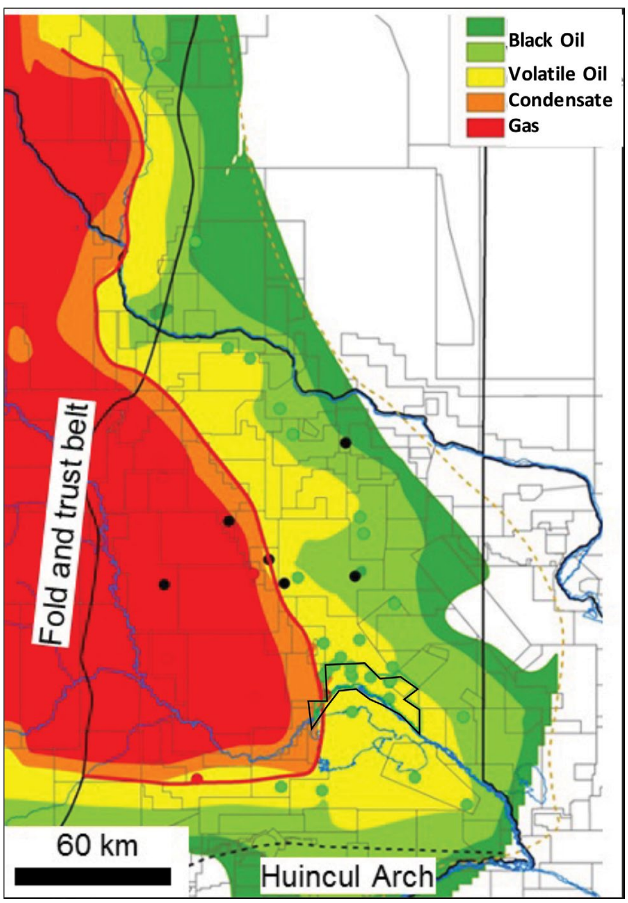

Figure 1. Loma Campana is located in the Central area of Neuquén Basin, predominantly in the volatile oil to condensate windows. To-date, Loma Campana is the most data-rich Vaca Muerta Fm. exploitation concession block, with more than 560 producing wells (430 vertical & 130 horizontal) and 3D seismic coverage in ~95% of the area.

conventional 3D seismic data. The objective of this study is to add a 3D seismic acoustic impedance volume into the static model characterization workflow to gain reservoir predictability in 3D space. Mid- and long-term applications of this product include prospective areas identification, landing point selection, rock-types distribution for geosteering planning, and full-field development prioritization.

METHODOLOGY & RESULTS: RESERVOIR MODELING WORKFLOW

Structural and stratigraphic modeling

In order to build the stratigraphic framework, we used resistivity logs for identifying stacking patterns, and sonic and GR logs as proxies for facies to help in the differentiation between carbonates and organic-rich facies. 3D seismic horizons as well as a Vaca Muerta Fm. depositional conceptual model (bottomsets-foresets, Reijenstein *et al.*, 2017) were used to validate and guide well top correlations on over 150 vertical wells. Average distance between wells is approximately 1.5 km.

The first step in the model construction was to define the main bounding surfaces for the stratigraphic framework. For this purpose, it was decided that the faults and main surfaces should be modeled using a Volume Based (VBM) approach in Petrel. The technique allows to have an exact tie of the seismic horizons with the well tops ensuring layer's volume consistency and allowing minor framework adjustments to avoid mismatches (Vargas *et al.*, 2017). In addition, it helps with areas of scarce data, where no interpretation is possible due to bad seismic quality. Due to abrupt changes in thickness along each progradation the initial VBM model presented limitations to solve the whole structural framework, although it was used to generate critical surfaces. For the final version of the model a conventional approach using pillar gridding in Petrel was selected.

The surfaces for the structural framework were top of Catriel, top of Organico Superior, top of progradacion 3 and Nivel Q. The internal surfaces were modeled using a pillar based approach. This approach uses the well tops as hard data and it forces the resulting surfaces to conform to the main bounding surfaces. The result model contains fifteen (15) surfaces and thirty-four (34) faults (Fig. 2).

To capture the geological detail needed for facies and petrophysical modeling, the layering scheme selected included geological layers of around one meter (1m). This put the total size of the grid in 110 million cells, sub-divided in 14 zones. Although seismic shows apparent downlapping of the prograding clinoform seismic reflectors into underlaying layers, well data shows that layers do not pinch out completely. Therefore, the model's layers follow the shape of the prograding clinoforms but never downlap completely into underlaying tops. This characteristic made the layers in the bottomsets very thin (from 0.3 to 0.5 meters).

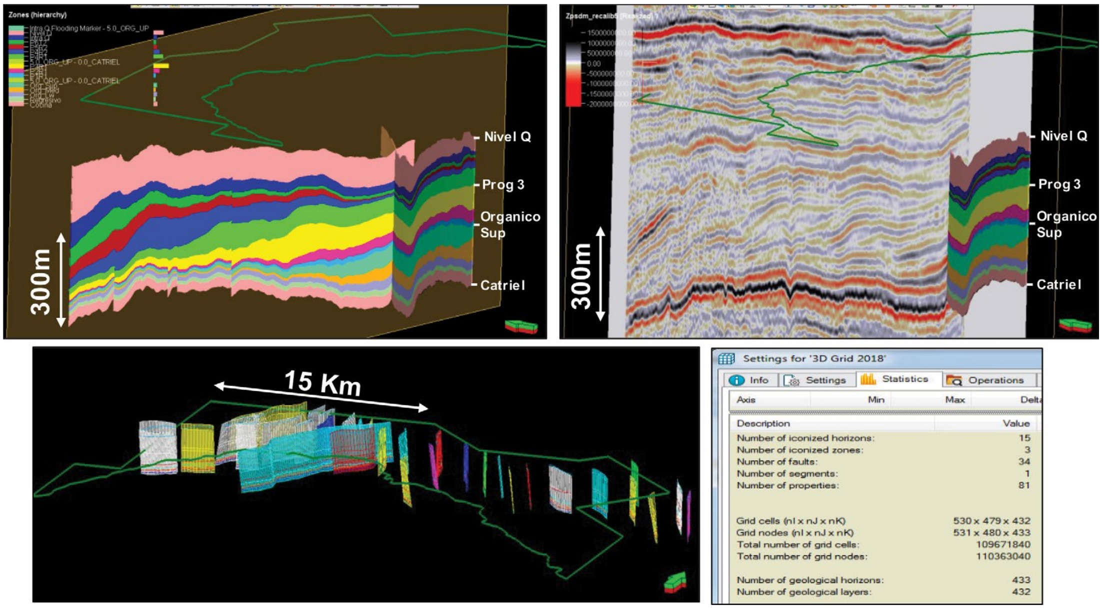

Figure 2. Static model's structural & stratigraphic model containing 15 surfaces and 34 faults

Facies modeling

Based on the electrofacies workflow shown by Crousse *et al.*, (2018, this congress), we defined 8 electrofacies or rock types with distinct ranges of TOC, PHIT, and AI values. Five of those e-facies correspond to Vaca Muerta Fm. organic-rich lithologies, whereas the remaining three belong to the calcareous Quintuco Fm. facies. Figure 3 shows an outstanding good visual correlation between well AI, E-facies, and 3D seismic AI, using a uniform color palette, and displaying the organic-rich Vaca Muerta Fm. facies in warm colors (brown, red, orange, yellow, green). This visual correlation encouraged us to use the 3D seismic inverted acoustic impedance volume as a tool for predicting rock types away from well control. Inverted AI volume was generated using 19 wells.

As a second step, we cross-plotted "upscaled well AI" versus "3D seismic resampled AI" property per stratigraphic layers to measure and quantify the degree of correlation between these two datasets. Results showed high correlation coefficients (>0.65) for the upper Vaca Muerta Fm. and lower correlation (<0.5) for the basal section of Vaca Muerta. Some challenges faced in the lower section relate to reduced seismic vertical resolution and subtle layering mismatch with respect to background seismic amplitude/impedance, generating lower well-seismic correlation coefficients, especially in thinner layers. Conversely, the higher acoustic impedance contrast between layers on the prograding middle and upper section allowed us using the 3D AI volume for facies population.

Since each electrofacies has different well acoustic impedance ranges (e-facies versus AI bar chart in Fig. 3), we defined well-based AI cutoff value-ranges to each electrofacies and therefore were able to tie 1D well e-facies with 3D AI volume values. Part of this workflow included using

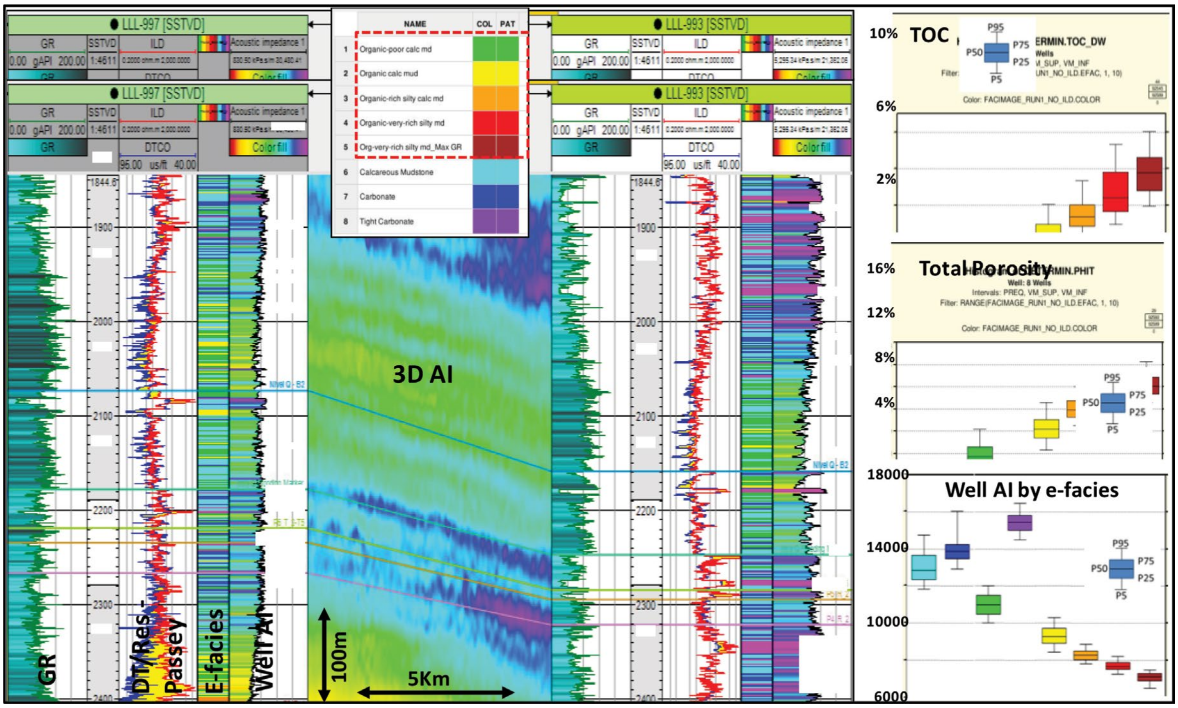

Figure 3. Correlation between well AI, E-facies, and 3D seismic AI, using a uniform color palette, and displaying the organic-rich Vaca Muerta Fm. facies in warm colors (brown: organic-very-rich silty mudstones (max GR); red: organic-very-rich silty mudstones; orange: organic-rich silty calcareous mudstones, yellow: organic calcareous mudstones, green: organic-poor calcareous mudstones, cyan: calcareous mudstones, blue: carbonates, violet: tight carbonates). On far right, note bar charts displaying 8 discrete e-facies on x-axis and property ranges (TOC, PHIT, AI) on y-axis (Colored box = percentiles 25% to 75%; lines = percentiles 5% to 95%).

probability curves to capture the likelihood of occurrence of one facies over the other in areas with overlap of AI values. Once this step was completed, we co-kriged the well input with the seismic-resampled 3D acoustic impedance volume (AIV) to generate a facies model.

We also tested a second approach for facies population to evaluate, measure, and find the best predictive model for facies prediction. The second approach included the same workflow but instead of applying the 3D AI volume to guide 3D facies population, we used higher resolution well AI data points (~150 vertical wells) together with the 3D AI volume (as a soft constrain only) to generate a pseudo-AI volume (AIW), with which we then populated facies (Fig 4).

In order to quality check both models and perform a predictability blind test, i.e. repopulate the model leaving out some wells to compare with original populated model, we left 14 wells (from a total of 74 used wells) outside the facies modeling workflow. Correlation coefficients show up to 0.72 predictability in upper layers and down to 0.45 in the lower ones, especially the thinnest. These coefficients were calculated on a cell by cell R2 comparison basis, by comparing upscaled well e-facies property vs. AI seismic-derived facies property extracted at the “blind” wells, per stratigraphic framework zone. Comparing one model versus the other, the AIV approach is the best facies predictor in the upper Vaca Muerta section whereas the AIW approach resulted in better prediction towards the basal layers. The most likely explanation for this behavior is that

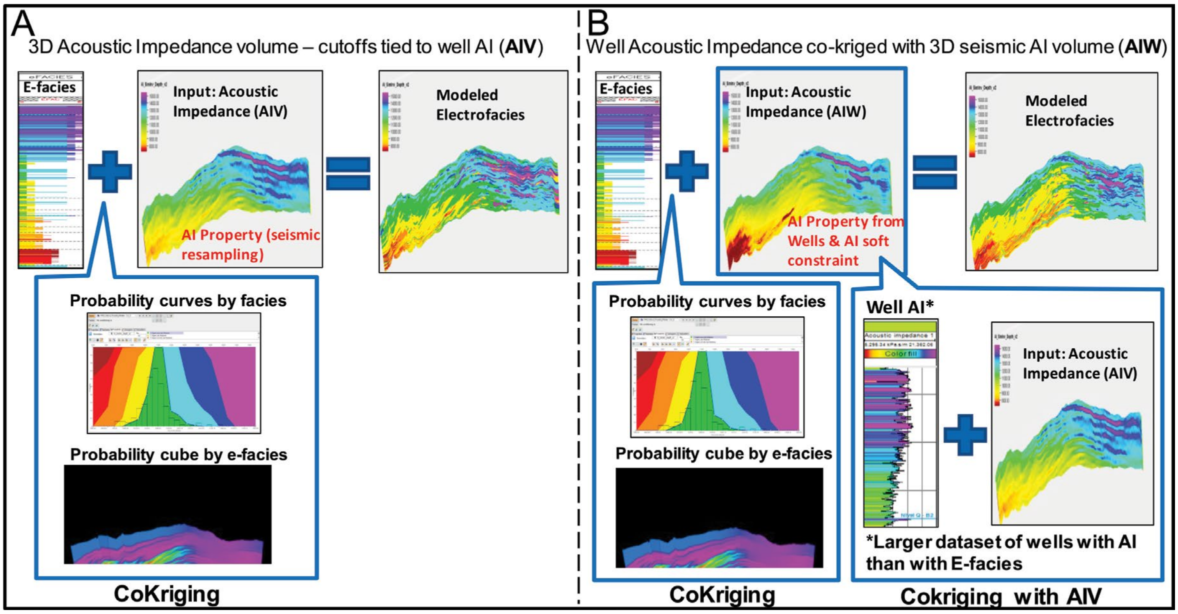

Figure 4. Two different approaches for facies population. On the left, we used well e-facies together with the 3D seismic AI property (AIV) derived directly from the 3D AI volume (seismic resampling) to generate a facies model. On the right, we also used well e-facies but instead, we generated a 3D AI property based on ~150 wells with AI and using the 3D AI volume as a soft constrain only (AIW).

the AIW model, which is strongly influenced by higher resolution well AI data, is being able to resolve facies below seismic resolution in the homogeneous lower section. On the upper layers, the AIV model, which is highly influenced by the 3D AI volume, is able to resolve thicker and acoustically heterogeneous lithologies and therefore is acting as a better predictor for estimating facies distribution.

Property modeling

The final step on the reservoir model workflow presented on this study consisted in modeling different rock properties by using a closure matrix model. The model inputs are a set of equations that uses compressional sonic, deep resistivity, density and neutron porosity logs as input to calculate TOC, porosity, and main matrix content (discriminated as total Carbonates, total Clays and Quartz-Feldespar-Mica) (Cuervo *et al.*, 2016).

The distributions of the input properties are all based on well data, but two scenarios were run: one based on log population by facies, and the other one without constraining to facies. In both cases the preferred population algorithm was Kriging.

This approach was used for compressional sonic and deep resistivity. However, for density, the extrapolation of sonic was used as soft constraint (co-Kriging). To populate neutron porosity and density, the acoustic impedance cubes were used as soft constraint. Figure 5 shows a simplified workflow diagram.

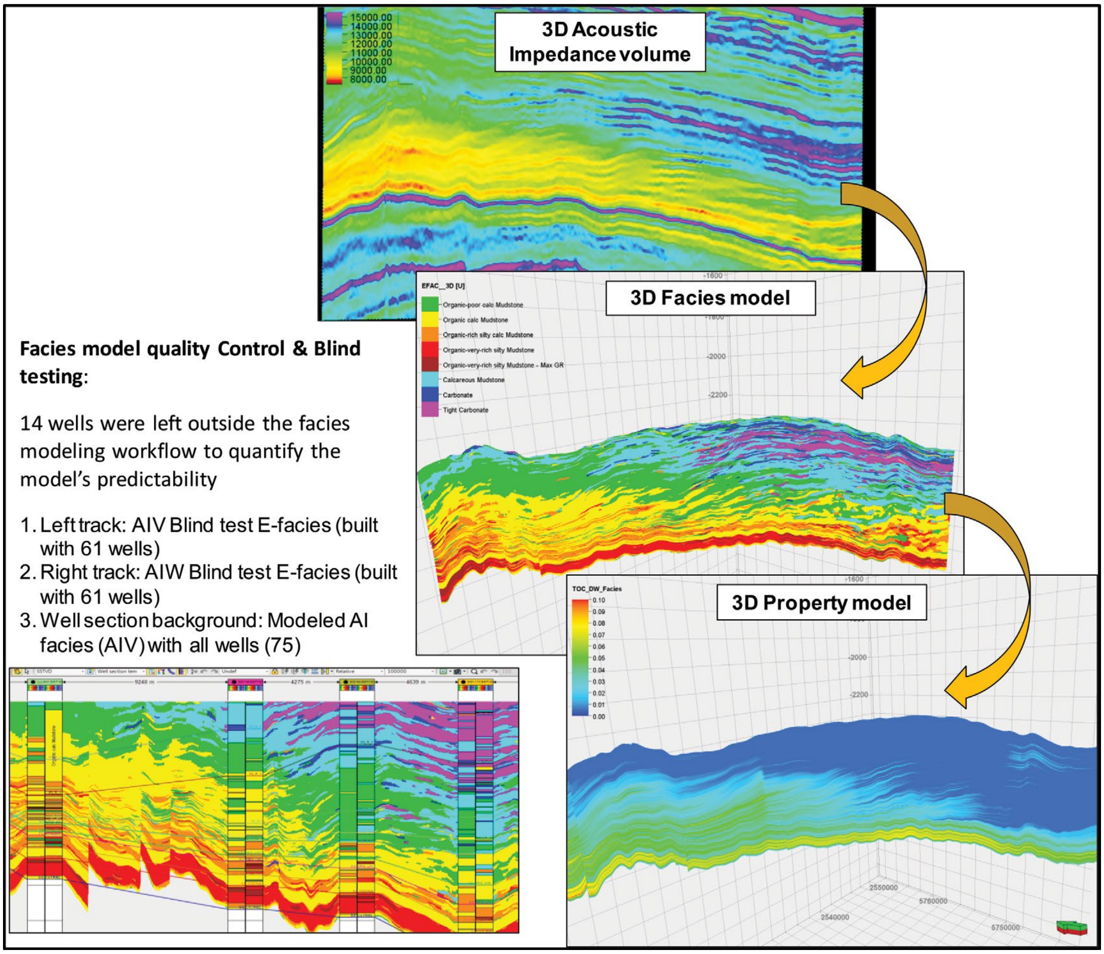

Figure 5. Simplified reservoir modeling workflow using 1D and 3D acoustic impedance data to model and predict facies and properties away from well control. Both facies and static property results show a strong control from the original 3D acoustic impedance volume as expected.

In order to validate the population of the properties in the closure model (Cuervo *et al.*, 2016), blind tests were performed in the same way used for facies model. The correlation coefficients show up to 0.95. It is worth to notice that for the property model we have more than double the number of logs used for the facies model, reducing the uncertainty.

APPLICATIONS

Currently the model is being used by the joint YPF-Chevron team to evaluate well proposals in the progradational section, which is where the model has higher predictability. The main applications are: reservoir properties prediction and optimum landing point definition for production optimization in Loma Campana Block. The model provides easy-to-generate deliverables as: average static properties values per layer, property maps, sweet spot delineation, and the ability to distinguish between carbonate-rich regressive progradational layers versus more organic-rich transgressive progradations. Ongoing work includes a 2nd phase of modeling that will integrate new acquired 3D seismic and newly generated acoustic impedance volumes (with higher resolution) into the workflow.

CONCLUSIONS

Integration of multiple scales of data, i.e. 3D seismic interpretation, acoustic impedance volumes from seismic inversion, well logs from more than 150 vertical wells and learnings from core data, allowed us to build a static model with a strong facies control based on well electrofacies and seismic acoustic impedance.

Impact of Static model on Shale reservoir prediction:

1. Using AI seismic volume & facies allowed us to reduce uncertainty in properties population away from well control, especially in the upper section of Vaca Muerta Fm.
2. Electrofacies-acoustic impedance integration allowed defining 8 seismic facies or rock types, which have distinct reservoir property ranges (PHIT, TOC, mineralogy, Young modulus, etc)
3. Current static model, based on AI seismic facies focuses on reservoir prediction for optimum landing point definition in Loma Campana block.

Lessons learned and Best Practices:

1. 3D seismic acoustic impedance (AI) has been key to model Vaca Muerta Fm. (VM) facies and be able to predict rock types in 3D space, throughout the Loma Campana Block
2. VBM (Volume-Based Modelling) was tested but was not the optimum method for structural modeling due to the prograding clinoform geometries of the Vaca Muerta Fm. sequences (quick thinning, downlapping, and seismic pinching out). Best approach was to use VBM to generate quick concordant faulted surfaces and then export framework to pillar gridding, which was the final structural method used.
3. Pillar gridding successfully handled clinoform thinning-out sequences and faults (15 layers and 34 faults)
4. Blind testing as quality check was a key best practice for quantifying model's predictability.

Challenges:

1. Subtle horizons mismatch between amplitude volume (for framework building) and AI

volume (facies) generates low well-AI seismic correlation coefficients, especially in thinner layers.

2. Although abundance of well control (more than 150 wells) is good for narrowing subsurface uncertainty, VBM generated intersecting surfaces while trying to honor many well tops. It worked best when using only 3-5 key horizons as input and the remaining 10-12 horizons were set "conformable" to well tops.

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