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Developing a regional Montney mineral model solution and applications for well placement optimization: A case study from NEBC

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Abstract

This study focuses on developing and applying a regional Montney mineral model solution to optimize target placement and understand production results in Northeastern British Columbia (NEBC). It details the model's calibration process, the inputs used, the minerals and fluid volumes solved, and addresses data limitations with recommendations for optimal calibration. The model specifically examines the role of calcite in production performance and identifies beneficial mineral associations. Using an AI-enabled multimineral software tool combined with petrophysical expertise significantly reduced the time required compared to traditional methods. Calibration utilized Elemental Capture Spectroscopy (ECS) logs and core data from ten wells, blind tested on five wells, and applied to 268 wells in the region. Uncertainty maps and curves were created to assess data reliability, factoring in proximity to logs and core samples, log normalization, and model non-uniqueness. These tools help flag areas of varying confidence levels, aiding the asset team in their workflow. The mineral model results are now routinely used by the asset team to refine landing zones and guide well placement decisions. A case study in NEBC demonstrates how the model improves reservoir characterization and optimizes well placement, enhancing hydrocarbon recovery and maximizing economic returns in the Montney play.

Statement of the background

The mineral modelling work was undertaken in an effort to explain lower than expected production results in the Middle Montey. Core analysis and advanced petrophysical logs supported a negative correlation between increased calcite volume and lower EUR. Data coverage was limited to 20 control points across the study area, a regional mineral model was proposed to characterize mineral variability away from core and advanced log control.

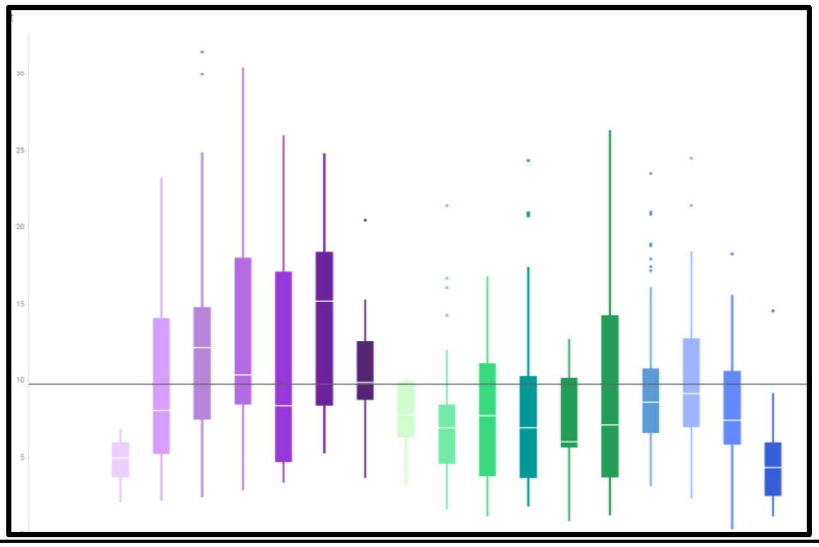

Figure 1 shows EUR against interval, the Middle Montney is shown in Green. EUR was lower than expected.

Aims and Objectives

The aim was to better understand the regional variation in mineral volumes and the relationship to production, providing geologists with a tool to optimize landing zones. Standard petrophysical analysis of porosity and water saturation did not provide sufficient information to refine landing zone selection.

Materials and methods

The area of interest counts with 268 wells with modern logs Gamma Ray (GR), density (RHOB), neutron (NPHI), photoelectric factor (PEF), and resistivity (RT). Ten of those wells count with Electron Capture Spectroscopy (ECS) logs which were inverted for mineralogy and calibrated using XRD results from four wells.

Semi-automated log normalization and corrections
Before the multimineral analysis was performed, a semi-automated log normalization was done to remove non-geologic features due to different vintages, drilling environment, and different logging companies. Due to drilling with heavy muds, the photoelectric factor required significant corrections to be used in the analysis. The photoelectric factor is a critical log when different carbonates (dolomite and calcite) are present and required to be solved for. Figures 2(a) and 2(b) show and example of the normalization process done to correct the PEF logs (2(a) before and 1(b)after).

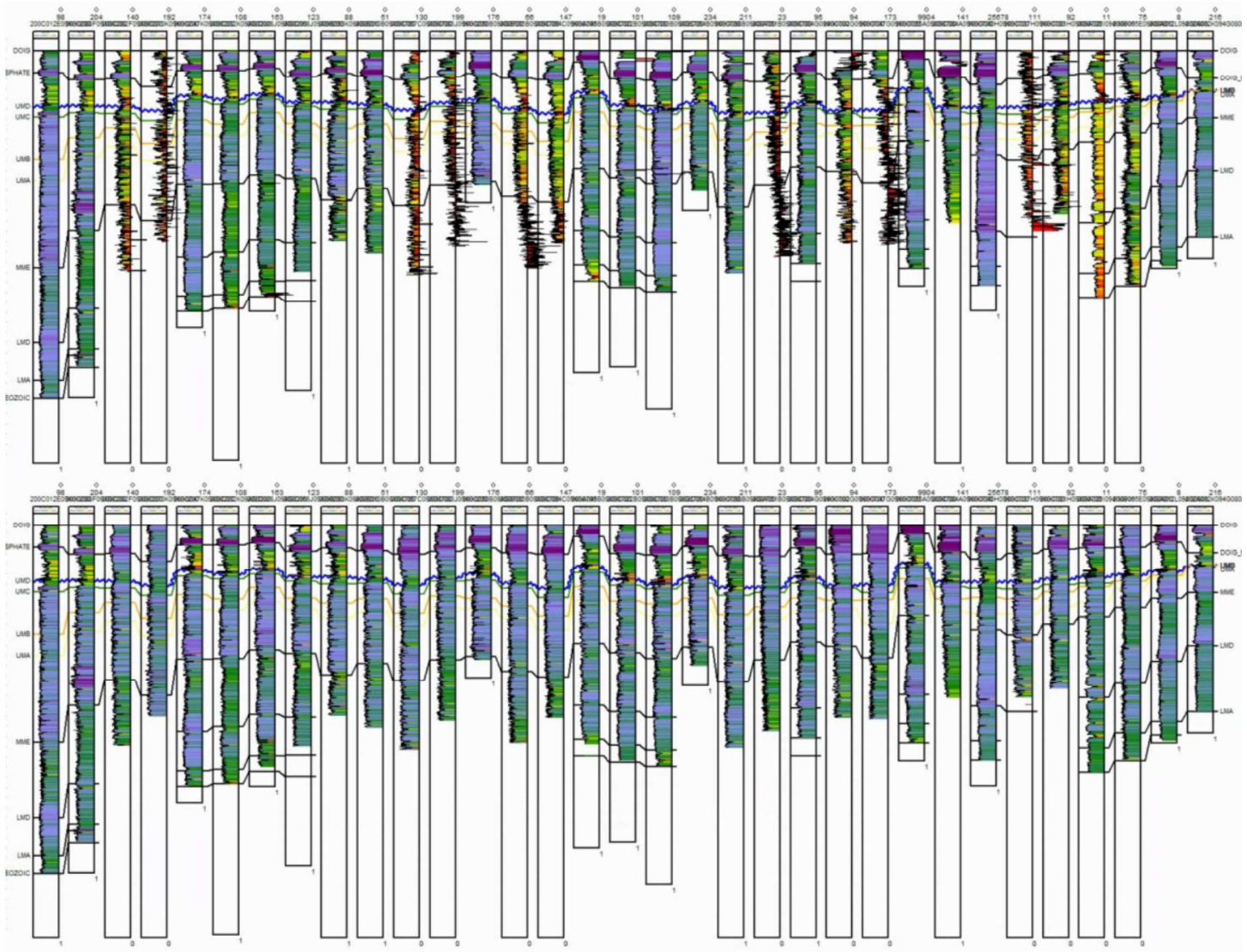

Figure 2 (a) before and (b) after

Multimineral Analysis

The complex mineralogy composition of the Montney formation, coupled with the limited number of logs in most wells, necessitates solving of mineral mixtures rather than individual minerals. Solving for mineral mixtures requires extensive refinement of mineral endpoints. To facilitate this process, the mineral model was developed utilizing an AI-enabled multimineral software tool that uses a genetic algorithm engineered to estimate minerology and fluid compositions in complex reservoirs (Michelena et.al. 2020).

Typical multimineral analysis requires the user to input the log properties (end-points) for each of the pure components of the rock. In complex reservoirs this task becomes difficult as there are many minerals present. In the area of the study, X-ray diffraction data (XRD) and total organic carbon analysis (TOC) of the Montney formation indicated the presence of at least twelve minerals (quartz, K-feldspar, plagioclase, calcite, dolomite, siderite, apatite, pyrite, chlorite, Illite, kaolinite, and kerogen). Calibration was achieved using results from Elemental Capture Spectroscopy (NEXT) logs and core data in ten wells, blind tested on five wells and applied to 268 wells in the area.

While the Elemental Capture Spectroscopy (NEXT) tool solves for mineral and kerogen components of the rock, its application was limited due to the small number of wells with this data. These wells were used for calibration points for the mineral model, enabling a robust regional multimineral solution.

The initial step involved analyzing the XRD data to determine which rock components to solve for based on their abundance and the project's objectives. Preliminary observations indicated that increased calcite volume was associated with lower EURs and impacted geomechanical behavior during completion. Given these relationships it was critical to solve explicitly for calcite in the mineral solution. Due to the high variability, quartz and dolomite were also important parts of the solution, similarly with clays and kerogen. The primary focus of the model was to predict the amount of calcite in the rock.

Although the remaining minerals were not explicitly solved for, they must be included within other minerals (as mineral mixes) because their presence affects the logs and needs to be accounted for. To achieve this, XRD analysis was conducted, and the relationships between minerals were corroborated to create mineral mixes. Figure 3(a) shows the relationship between quartz and total feldspars for one calibration well, while Figure 3(b) illustrates the relationship between clays and pyrite.

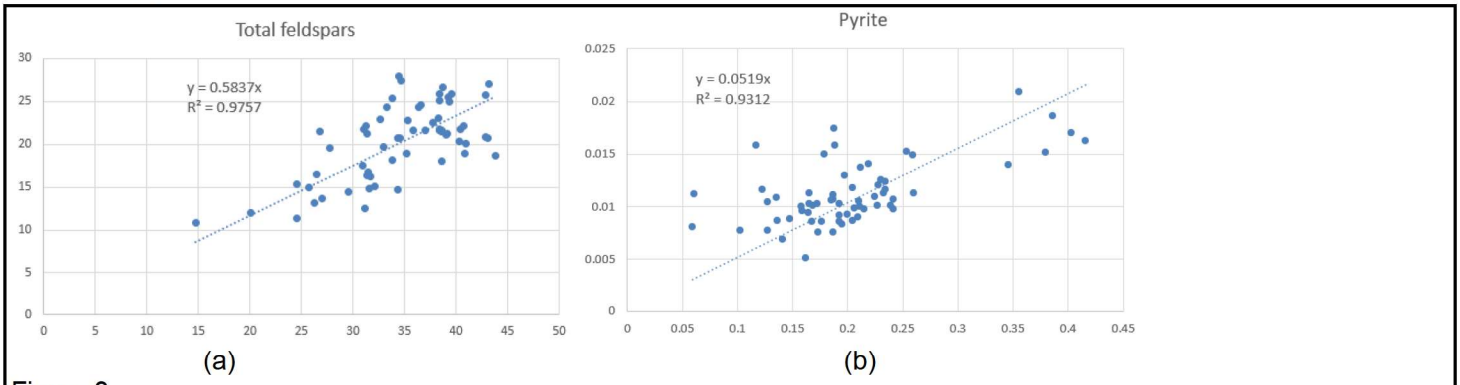

Figure 3

Many combinations of minerals were explored and together with modeling observations the final rock components solved for were: QFMs (quartz, felsdspars, and mica), dolomite (which is mixed with other heavy components like siderite), clays and others (Illite, kaolinite, and pyrite), calcite, and kerogen. Reducing the problem to five rock components and two fluids (seven components in total). However, the number of logs available is five plus the unity equation we get six equations, therefore we require an additional restriction or log to be able to solve the problem. The preliminary work done in the area using a deterministic approach to predict porosity and kerogen showed a very good correlation with core data, so after several test we decided to incorporate the porosity from deterministic methods to add an equation to the solution.

The second step is to decide if/how to split the Montney formation. Based on the iMineralysis optimization results, the Montney formation was split into three subintervals for modeling purposes (Upper, middle and lower Montney).

The third step is to find adequate end-points for the new rock components. As explained above, since we are mixing some of the minerals, the default properties reported in the software are not adequate. iMineralysis® allows to set limits to the rock component properties to be used by the genetic algorithm as it searches for a solution. The software tests hundreds of combinations of endpoints within the specified user defined ranges. Petrophysical and regional knowledge were essential to define these ranges. This application of AI and petrophysical expertise significantly decreased the time required to

complete the study compared to a classical mineral modeling approach. Figure 4 shows the comparison of the mineral models from ECS vs multimineral analysis.

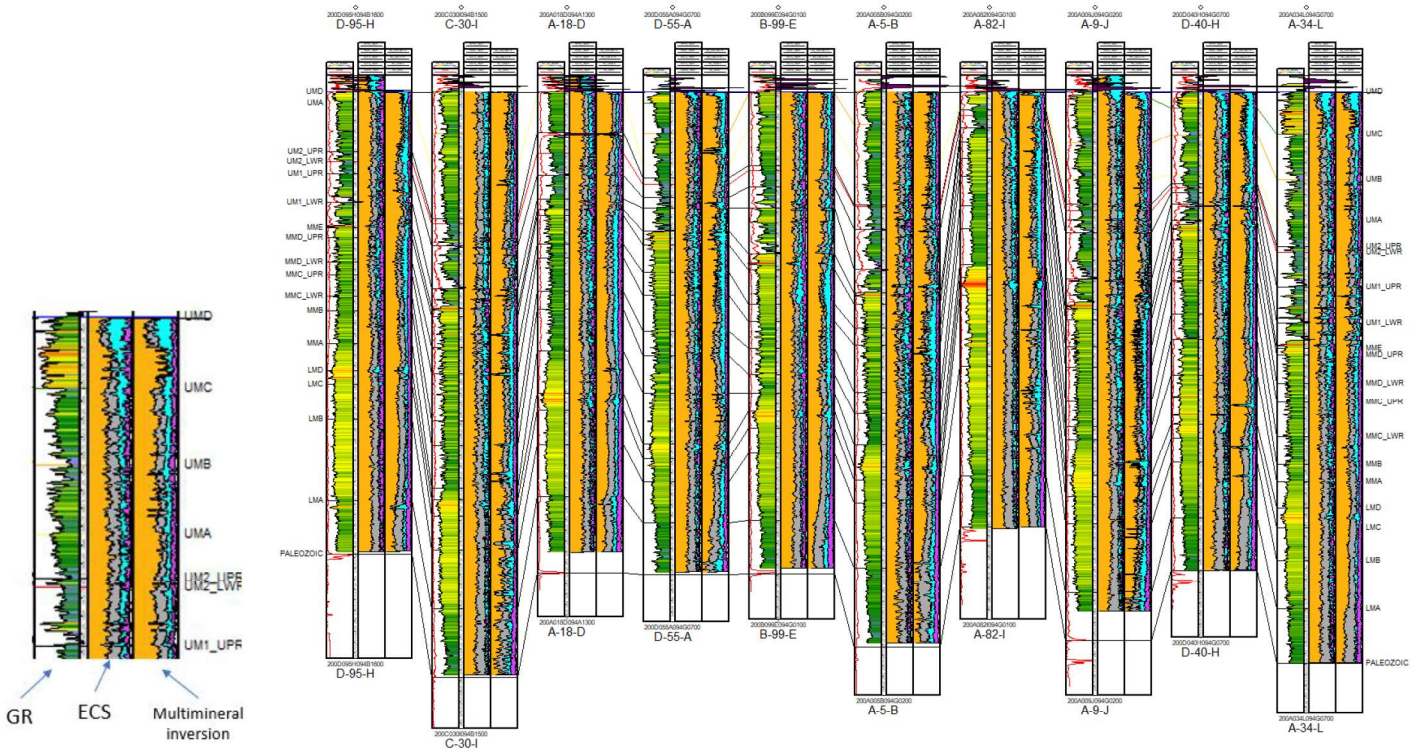

Figure 4

The fourth step was to determine a water saturation model for the area that statistically matched the water saturation measurements from core. For this area we used a modified Archie's model with m and n equal to 1.8 and salinity of 140 Kppm. We used a fixed temperature gradient model with depth to calculate water resistivity (Rw) from salinity.

The fifth and final step was to generate uncertainty maps and curves were generated, taking into account various factors such as proximity to well logs, proximity to calibration wells, degree of log normalization, and the inherent non-uniqueness of the multimineral model. The maps were constructed to evaluate the reliability of the mapped data across the area. The curves were created to flag areas of high, medium, and low confidence to complement the asset team workflow.

1) Proximity to calibration wells: distance to wells with core and/or ECS logs.
2) Level of log normalization: percent normalization of all logs with respect to the original log data. A global indicator was estimated using the average for all logs.
3) Inherent non-uniqueness of the multimineral model: end-points are calculated using five different seeds for the genetic algorithm and average and standard deviation of the realizations is estimated for each mineral output.

Results and discussion

Mineral modelling results were generated in approximately 270 wells, producing regional mineral control across the study area. The results are now standard in the geologist tool kit for landing zone selection. Landing zones are selected on the basis in part on their mineral composition, well results have improved with targeted zone selection and geosteering to remain in zone. Full integration of the data is still ongoing and results to date show correlation between mineral composition and EUR. Initial results show the highest EUR wells correlate to highest QFM and lowest Calcite.

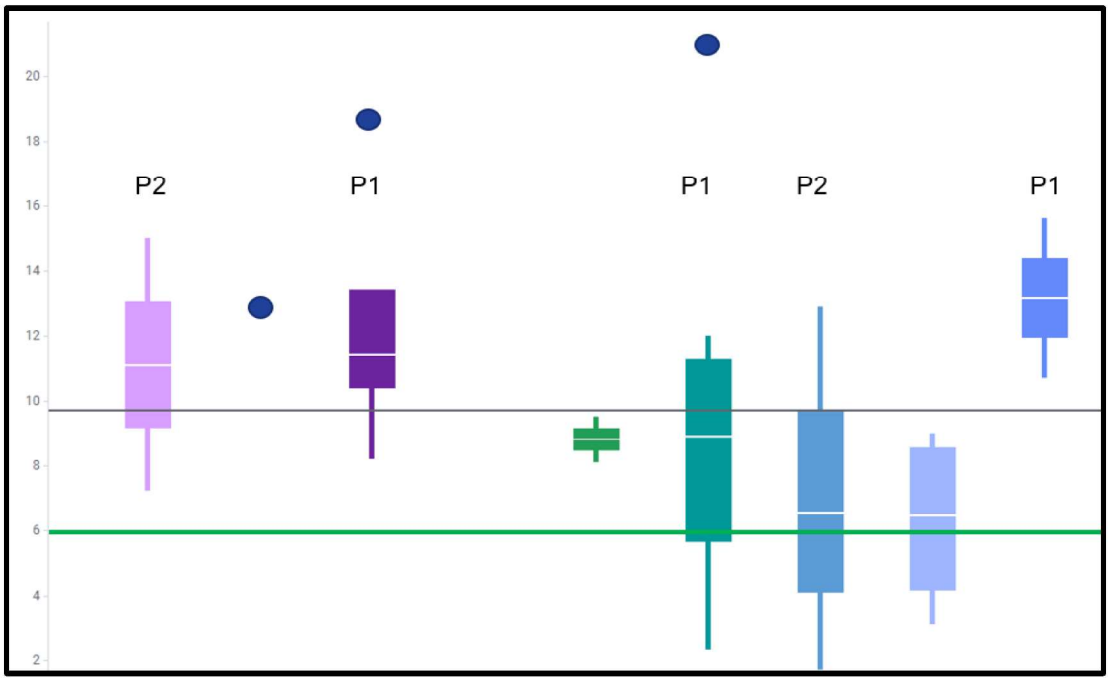

Figure 5 identifies 3 primary and 2 secondary targets within the area which correlate to low calcite and high QFM volumes.

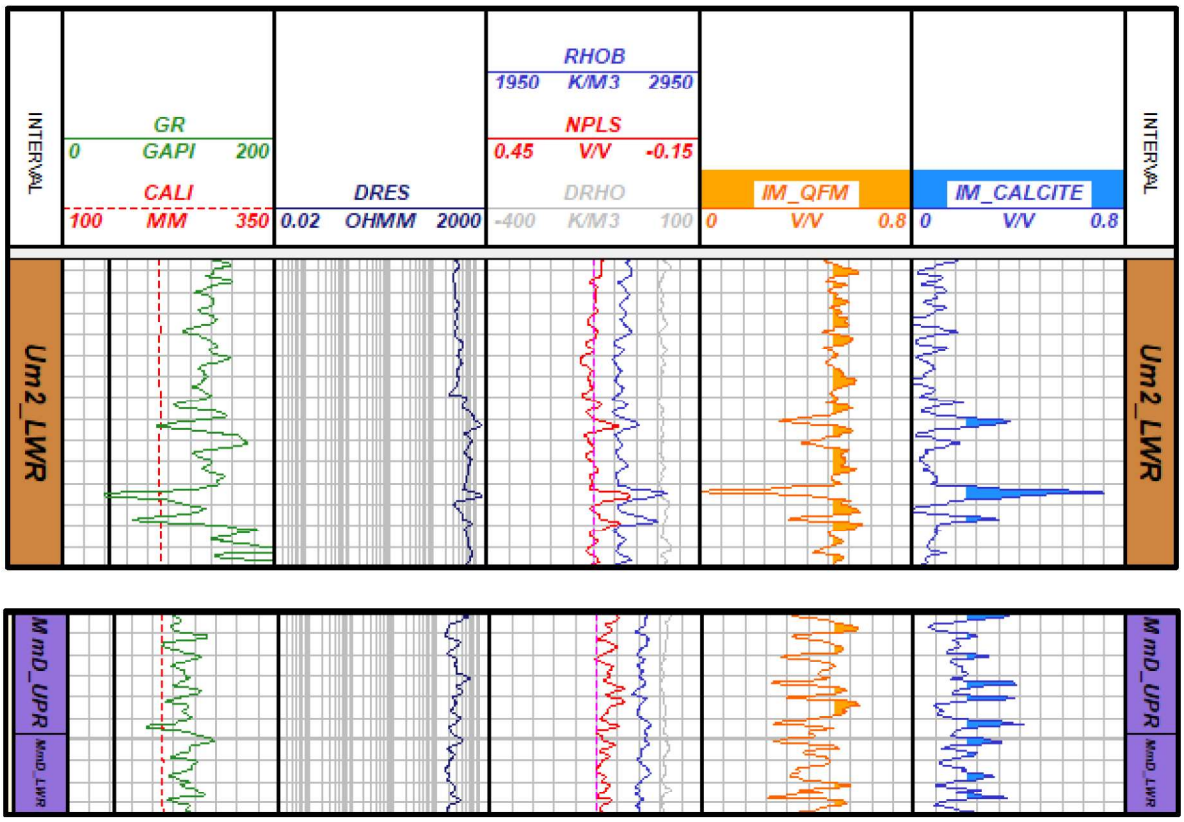

Figure 6. Primary targets have the highest EUR or lowest variability within their interval. Below is an example of a P1, high QFM low calcite log signature contrasted with a lower EUR interval with lower QFM and higher calcite.

Uncertainty results

Figure 7 (a), (b) and (c) shows the results of the three components of uncertainty studied (a) normalized distance to calibration wells, (b) degree of normalization of input logs and (c) average standard deviation of the minerals in the mineral model. In Figure Y, we show two possible combinations of the uncertainty maps to determine a global uncertainty map for the area. Figure Y (a) shows an equal weight combination and figure Y(b) shows 10% weight to the distance, 40% to normalization and 50% weight for the mineral model. These maps helped identify which areas have larger uncertainties in the model.

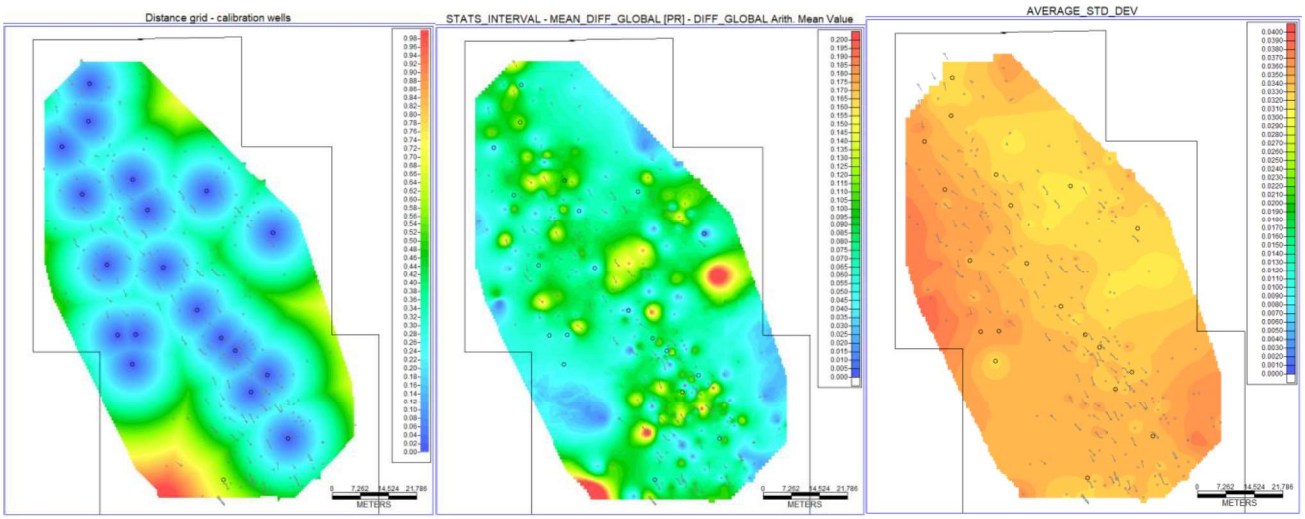

Figure 7 (a) Normalized distance to calibration wells (b) Degree of normalization (c) Average standard deviation

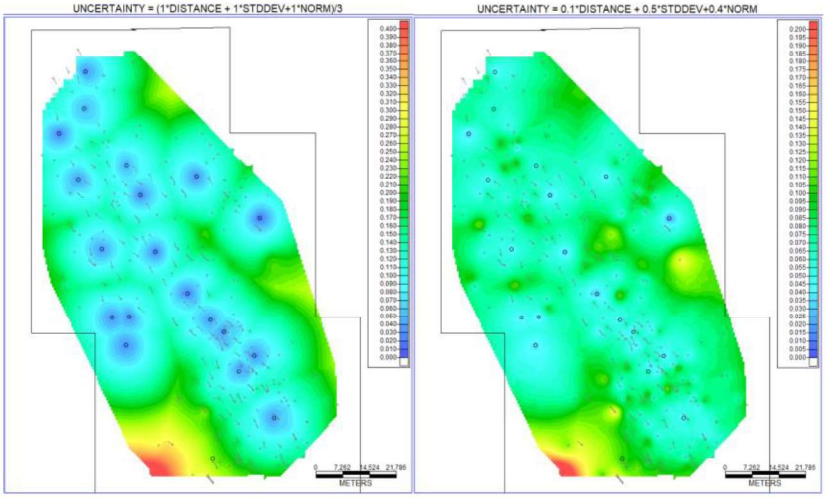

Figure 7 (a) Uncertainty = 1/3*Distance+1/3*norm+1/3*StdDev (b) Uncertainty = 0.1*Distance+0.4*norm +0.5*StdDev

Conclusions

The work achieved the initial objective of modeling the regional variation in calcite and offered valuable insights into other mineral components impacting well success.This methodology enabled rapid evaluation and calibration, resulting in a model applied to approximately 270 wells within the study area. The results provided control for mapping, Although integration of the results is still ongoing, the results have already proven valuable for geoscientists in optimizing landing zones and better understanding EUR. Future efforts will incorporate geomechanical modeling to further enhance the geoscience toolkit

References

Reinaldo J. Michelena; Kevin S. Godbey; Michael J. Uland; Patricia E. Rodrigues. Petrophysical multimineral analysis using genetic optimization to solve complex mineral composition in unconventional reservoirs. SEG International Exposition and Annual Meeting, Virtual, October 2020. SEG-2020-3425