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Automated Reservoir Model Calibration for Field Development Plan Evaluation Under Subsurface Uncertainty Applied to A Complex Multi-Zones Heavy Oil

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Categoría: Marque con una "X"

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Este artículo técnico fue preparado para presentación en el XIX Congreso Regional Colombiano de Petróleo, Gas y Energía organizado por ACIPET en Cartagena, Colombia.
Este artículo fue seleccionado para presentación por el comité técnico de ACIPET, basado en información contenida en un resumen enviado por el autor(es).

Abstract

Rubiales is a major heavy oil field in Colombia with an OOIP larger than 5000 MSTB (Stanko, and others, 2015). The field produces from six zones mainly with horizontal wells. Production is driven by a strong aquifer which causes tilted oil-water-contact and early water breakthrough. Fully integrated reservoir modelling for field development optimization under subsurface uncertainty has been a major challenge so far. This paper presents an automated calibration process, probabilistic infill well ranking and location optimization.

An automated reservoir characterization workflow was developed to generate multiple history matched models on field and well level. Static reservoir characteristics and contacts where parameterized for sensitivity assessments and calibration update steps. Variations of dynamic reservoir characteristics with an impact on model forecasting behavior were applied to alternative history matching solutions to create an ensemble of reservoir models for uncertainty assessment. Economic success criteria and a simulation opportunity index were defined for a probabilistic well ranking and optimized well location assessment.

The workflow was applied to a sector of the full field including approximately 300 producer wells. Multiple history match solutions were created with 80% of the producer wells matching on well level. Quality assurance measures were applied to verify geological consistency of implemented model updates.

The ensemble of forecasting models was used to deliver a probabilistic well ranking based on a well Net Present Value model. Infill well candidates with a robust performance delivery across the ensemble were identified. Results showed that a well placement scenario with half of more than 100 well candidates delivered above the economic threshold criterion and a similar recovery compared to reference field development plan. Probabilistic sweet spot maps based on a simulation opportunity index were used to efficiently identify well locations for more than 30 alternatives well candidates. The method produced robust results above the economic success criterion.

Methodology and workflow design developed in this work successfully delivered a field development evaluation under subsurface uncertainty for a large heavy oil field with complex geological characteristics, long production history and large number of wells. The workflow design is applicable for other fields with similar characteristics and delivery objectives.

The developing of this advanced workflow combined the application of a last-generation High-Resolution Reservoir Simulator (HRRS) and an Innovative Collaboration Environment (ICE) (Schlumberger 2020) which combines domain expertise and advanced digital technologies (ADT) enhanced quality and time results for history matching (HM) scenarios and bring the opportunity to execute several uncertainty cases for forecasting analysis allowing us to consider a wide range of results for final FDP proposed

Introduction

Rubiales Field is in the Southeast of Puerto Gaitán, to the East of the Departamento del Meta (Stanko, and others, 2015), approximately 310 km from Bogotá, as illustrated in Figure 1. It is the most important oil field in Colombia in terms of extension, original volumes, and production, it is also one of the most complex fields with different types of technical challenges

Based on technical discussions with the Rubiales Team, a collaborative project was designed to build a 3D model in a specific area of the field for dynamic and geological characterization of the reservoir, using new technologies. Optimization workflows in a multidomain software (Schlumberger 2020) were used for model calibration, that allows the interaction between geological and dynamic model using automated workflows. The general scheme of the solution is presented in Figure 2

About to the Regional geological configuration, the basin rises progressively in a West-Southeast direction, being affected by normal and inverse faults with variable displacements which are imperceptible in the seismic. The preferential course of these structures are NE-SW and N-S; These trends were identified in the structural style of the Rubiales field, as represented in Figure 3.

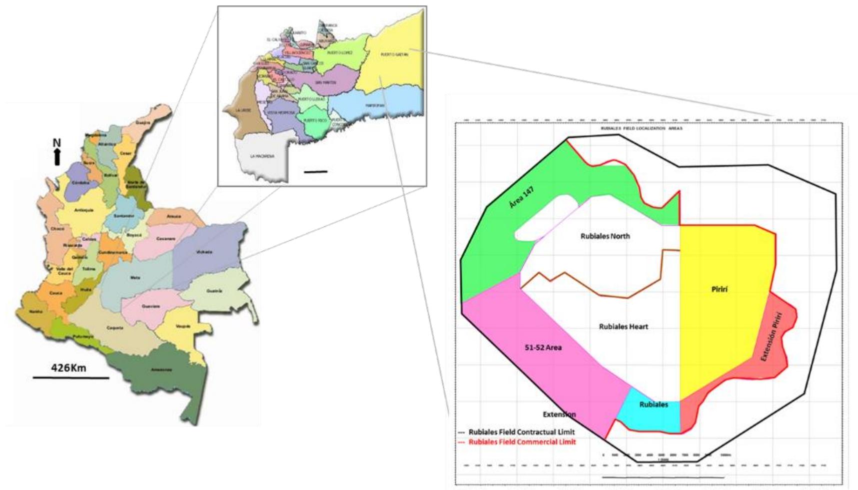

Figure 1. Rubiales Field Location

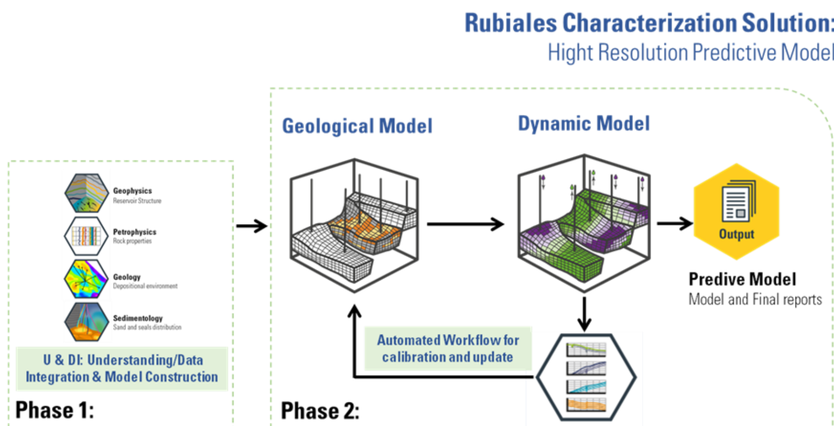

Figure 2. General scheme of the solution

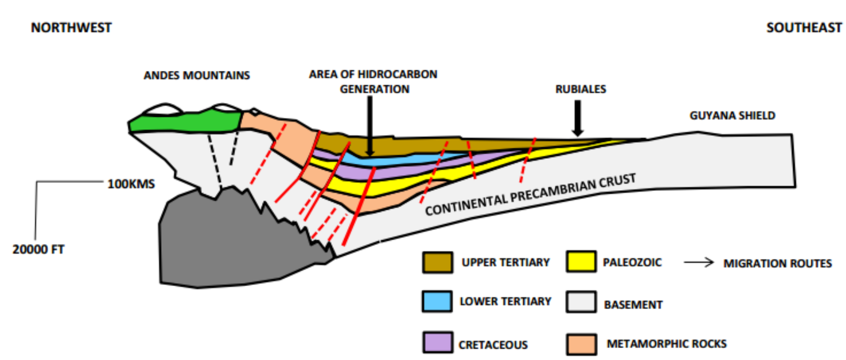

Figure 3. Regional geological configuration.

Methodology and Data

History matching

In this project a typical assisted history matching process was running initially, that include sensitivity and uncertainty analysis followed by an optimization algorithm. For the sensitivity process a big uncertainty matrix of 84 variables was defined covering static and dynamics parameters. The main variables were related with the OWC depth, relative permeabilities, aquifer properties and the seals distribution and properties. The definition of this matrix and its limits were agreed based on the statistics of the static model, literature, and the knowledge of the field

Once the sensitivity is completed, the most influence parameters were identified. After this analysis some variables were disabled and the uncertainty process was run with a Monte Carlo sampling considering only those parameters that are significant for the objective response, which is minimize the mismatch. With this process a case ensemble with a wide spectrum result was obtained, which allowed to redefine the limits and the distribution for the uncertainty parameters. The next step was focus on the optimization that is designed to improve the objective function value that should be minimized by tuning the set of input parameters remaining as active influencers. An evolutionary algorithm was implemented for the optimization that operates with three phases, in the first phase, simulation cases are distributed randomly in the search region, which gives an initial ensemble. Then during the second phase, the better simulation cases are retained, and the average objective function value is reduced, in the final phase, only the best simulation cases survive.

Even under a modern algorithm was applied, the matching results were not enough at the well level, however this workflow provided a good base case and the insights regarding of reservoir response which are the inputs for the next stage of history matching.

An innovator methodology was proposed and run, at this point it is well known those parameters that are significant. Vertical wells provided enough data to define the OWC depth, however this field has been developed by horizontal wells and these wells don't usually have information about this parameter. In that sense the OWC depth is being modified around the horizontal wells and it is changed based on the ratio of the water production in the simulation and the real water production, if the ratio is greater than 1 with 10% of acceptable error , it means that the well is producing more water than in reality and the OWC should be deeper, on the contrary if the well needs to produce more water the OWC should shallower, these changes are done in a region around of each well or group of wells until the mismatch is acceptable, Figure 4

$$\mathrm{R}_{Wrat} = \frac{Wrat^{\mathrm{Sim}}}{Wrat^{\mathrm{Hist}}}$$

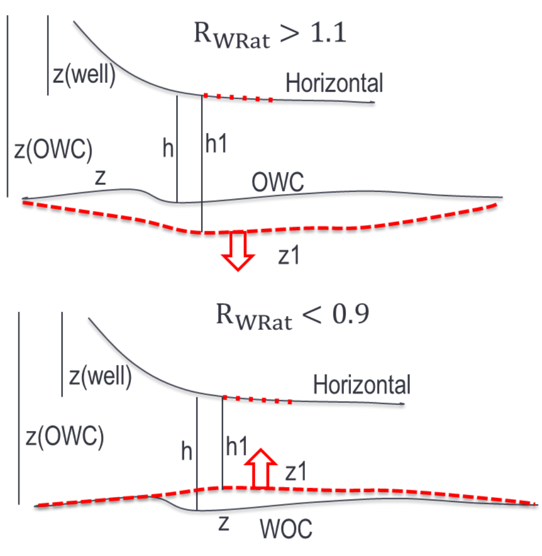

Figure 4. Solution Scheme for OWC change

The second parameter is related with the properties of the rock under producer zones, this intercalated zone could be or not a seal rock. As we are dealing with horizontal wells, they navigate through a zone, but the properties of the zone bellow are quite unknown for them. The solution proposed is a workflow that modifies the pore through radius in the rock for this zone based on the required water production, each loop will modify the rock properties around the proximal region for each well like the OWC solution approach. The influence regions for each well are created using the Voronoi algorithm that divides the space considering that each region contains the area that is nearer to one well than any other well. Like the previous case, if the well needs to produce more water the zone located below should be more permeable to allow more water to flow form the aquifer, otherwise this zone in the proximal region should be a seal. As the rock type is modified locally a geological control need to be done to ensure the trends and sedimentologic consistency, Figure 5

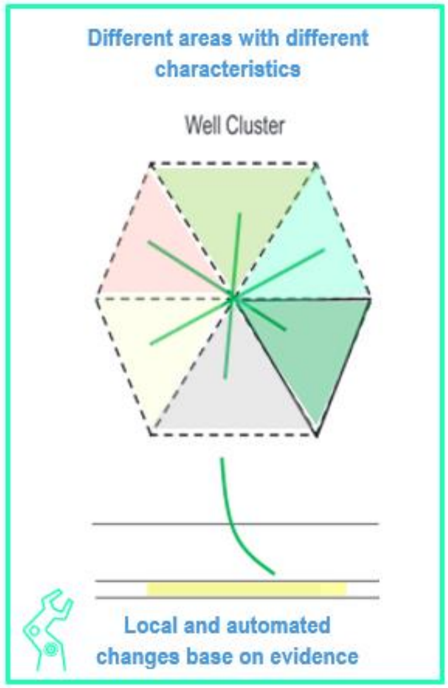

Figure 5. Solution Scheme for Seal properties change

Both parameters are changing simultaneous, the understanding is that the OWC depth impacts the water irruption time, and the permeability of the inter-producer zones leads how much water is flowing from below. As it is showed in the image, in the initial condition the well is not producing enough water, the zone below is blocking the water flow and the OWC is in a depth, in the final condition the zone became more permeable and the OWC is shallower which helps to minimize the mismatch, Figure 6.

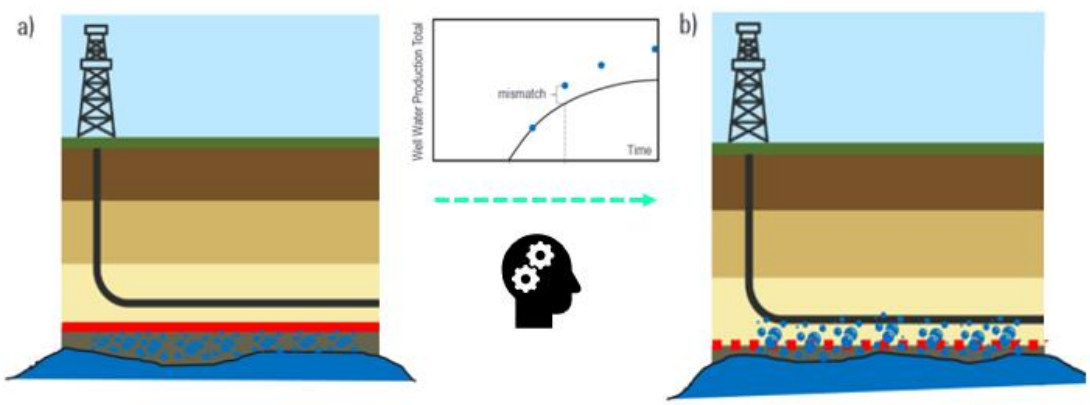

Figure 6. Solution Scheme for combine changes

Infill drilling - Uncertainty assessment

Once we have acceptable matched cases we started the forecasting process, as it is a mature field and the current FDP is focus on infill wells, to identify those zones that still have oil to produce is one of the most important tasks to be executed.

The first step was to evaluate the proposed wells initially, for that, a probabilistic assessment was executed for ranking these wells with hundreds of cases to capture the uncertainty model and quantify the impact in the well's objective (Schulze-Riegert, and others, 2020b). With this analysis the riskiest wells can be identified to generate a warning about their performance

The second stage is about to apply a complete automated and integrated workflow called accelerated field development plan shown in Figure 7 (Villarroel , Mendoza, Malibran , Quintero & Nuñez, 2021). This solution allows to run the main steps during an FDP design and evaluation, the first step is to have a calibrated model as was described in the previous section. The second step is about to create a

Reservoir Quality Index (RQI) (Khalil, Khazraji, & Shuker, 2015) and (Molina & Rincon, 2009), with the current reservoir properties considering the main productivity drivers in the field (Souche, Ghorayeb, Natela, Neog, & Dashti, 2016), with this RQI an automated target screening under uncertainty is run for each reservoir zone. Once the potential zones or targets are identified, thousands of wells possibilities with different trajectories, spacing, orientation, and lateral length can be evaluated in a fully automated way. After the workflow has found the potential targets based on the RQI, it creates the wells and run the simulation, at that time a performance evaluation needs to be run to determine what scenarios fit the best with the FDP objectives and constraints, finally for the selected scenario a probabilistic well ranking is done as a tool for decision making which allows to obtain what is the chance to achieve a certain objective for every single proposed well. The last step is about to design a risk mitigation plan aligned with the most impacting and unknown reservoir parameters

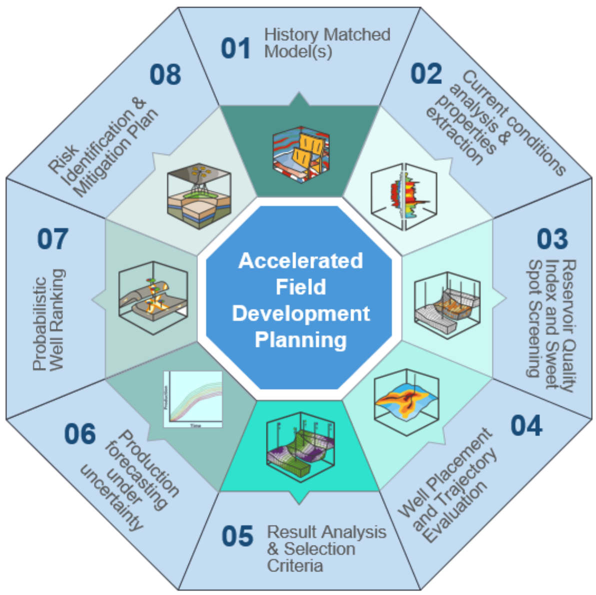

Figure 7. Big Loop solution scheme

Results and discussions

In this section we discuss history matching results and production forecast under uncertainty.

History matching (Sensitivity Analysis)

As we are dealing with dead oil, one the objective in this process is to calibrate the water production. To identify key calibration parameters a sensitivity study was launched with results shown in the tornado plot below. Oil water contact depth (OWC) and the intercalated seal properties were identified to be the main parameters which impact water production, Figure 8

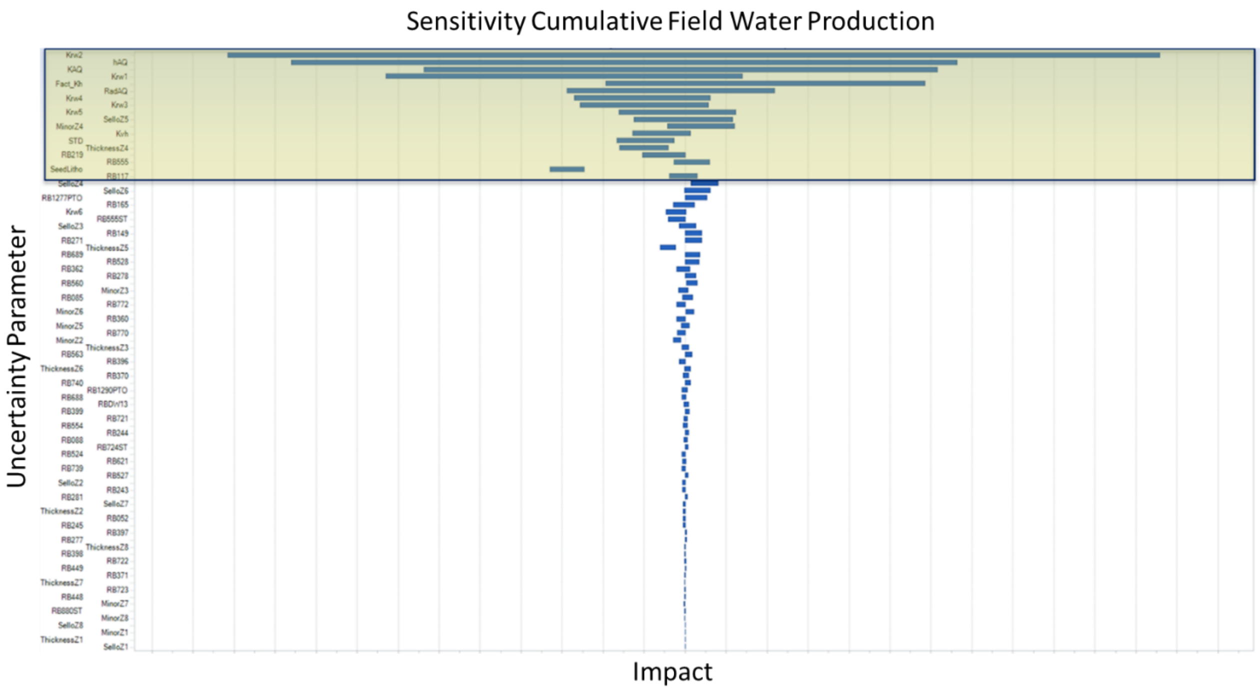

Figure 8. Tornado plot response for water production

As described above, in this step the variables with least impact were discarded and hundreds of uncertainty executions were done to cover the entire spectrum of possible solutions. The uncertainty spread of results for rates and accumulated oil, water, liquid and pressure are shown in Figure 9.

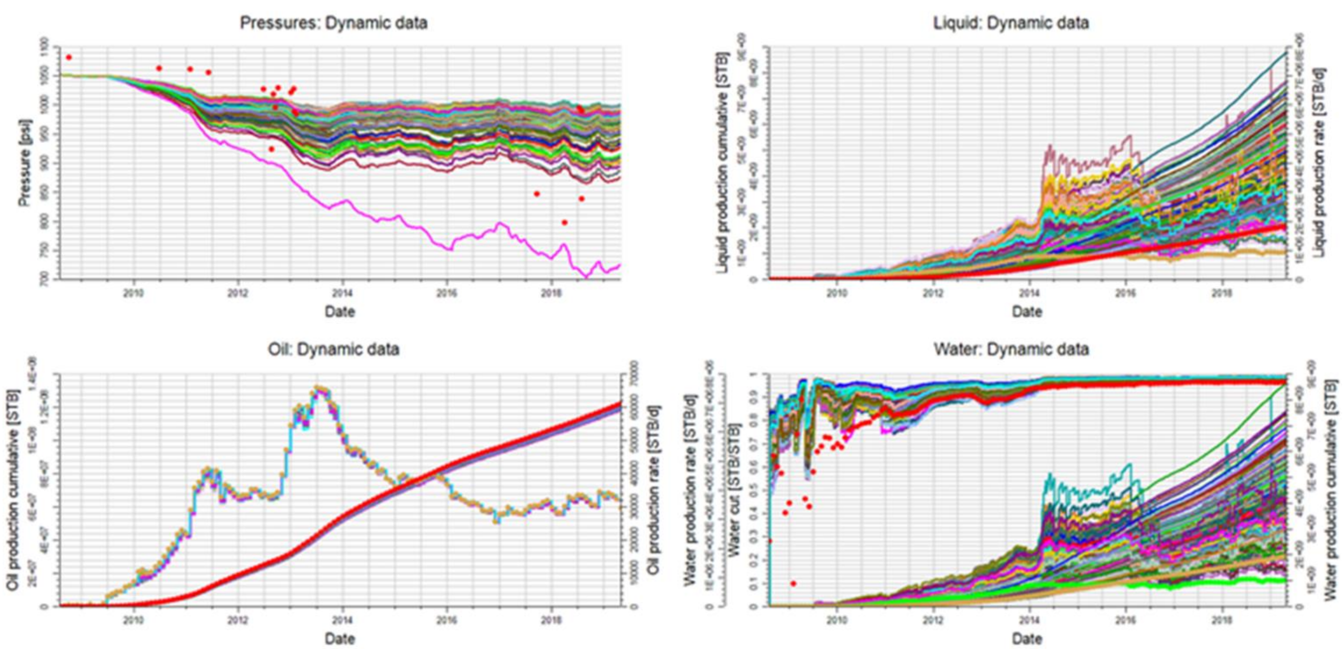

Figure 9. Uncertainty analysis for field rates and reservoir pressure (solid lines) compared to historical data (red dots)

The comparison of the best matched case (green line for water production rate) and the base case (purple line for water production rate) in Figure 10 was used to narrow down uncertainty parameter ranges in the model calibration phase using an optimization method (evolution strategy).

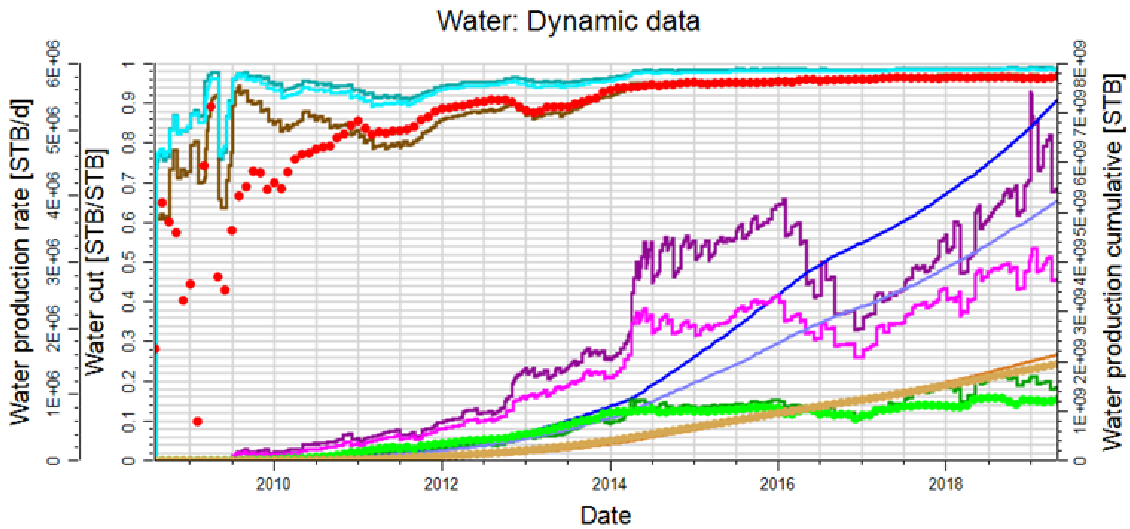

Figure 10. Base Case vs Best Case from Uncertainty Analysis

In the model calibration process, more than 200 simulations were launched using an evolution strategy which is an evolutionary optimization method inspired in biological principles. Parameter variation operators mimic evolutionary behavior and ultimately converge to an optimal set of solution candidates based on an objective function definition (Schlumberger 2020).

Figure 11 shows a best-case solution candidate identified so far. This case delivers an acceptable history match at full field level and will serve as base case for the final calibration phase at well level using an automated workflow design.

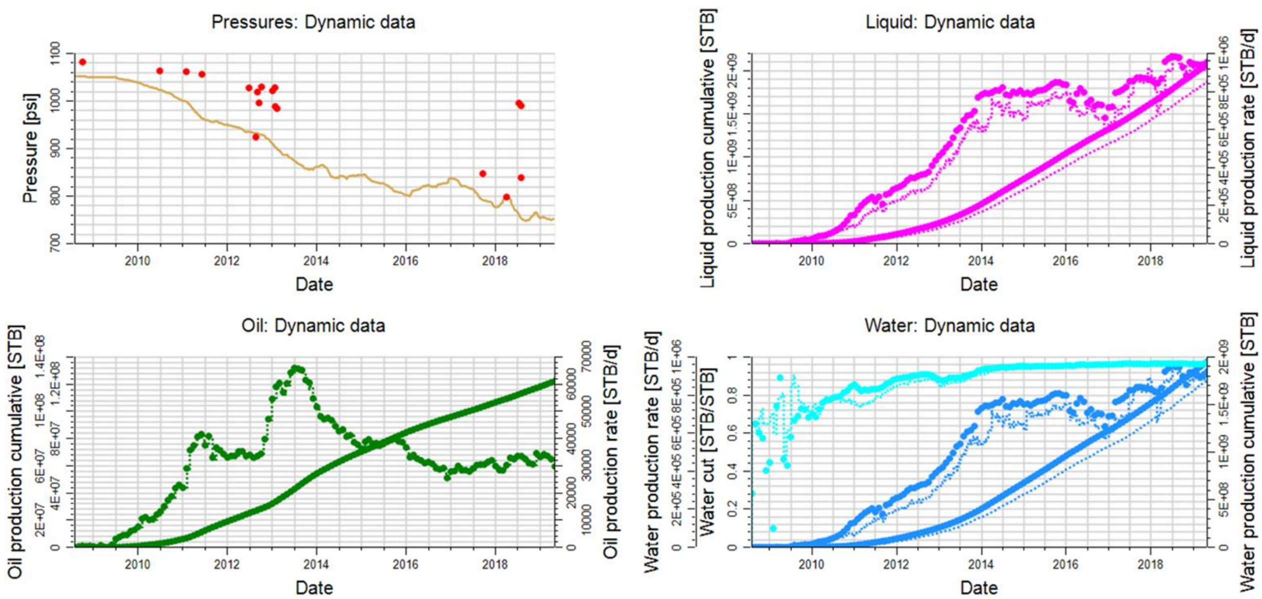

Figure 11. History matching results at field level. Simulation results (solid line) compared to historical data (dots).

Workflow automation for local history matching

The automated workflow design for local model updates explained in the first part of this document, delivered an acceptable field wide production history match (Figure 12) and in addition, 80% of all wells were matched among all considered cases, also illustrated in the mismatch map (Figure 13). This was considered to be a sufficient to move forward to a forecasting analysis,

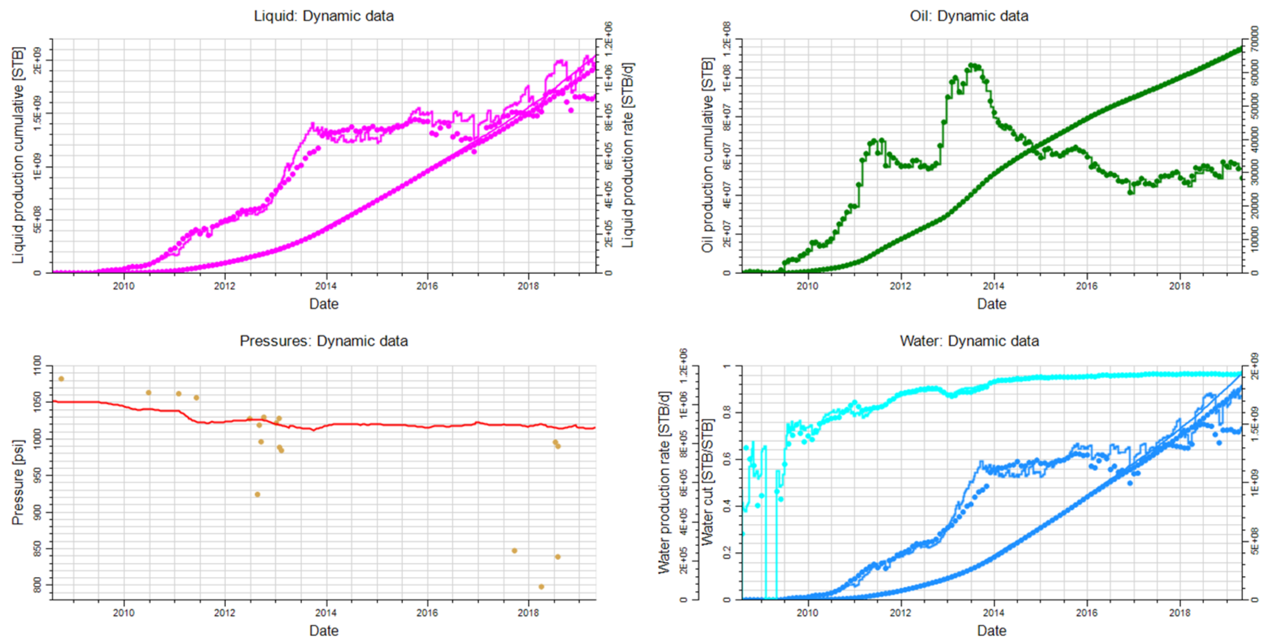

Figure 12. Refined history match at field level after running an automated history matching workflow at well level. Simulation results (solid line) compared to historical data (dots).

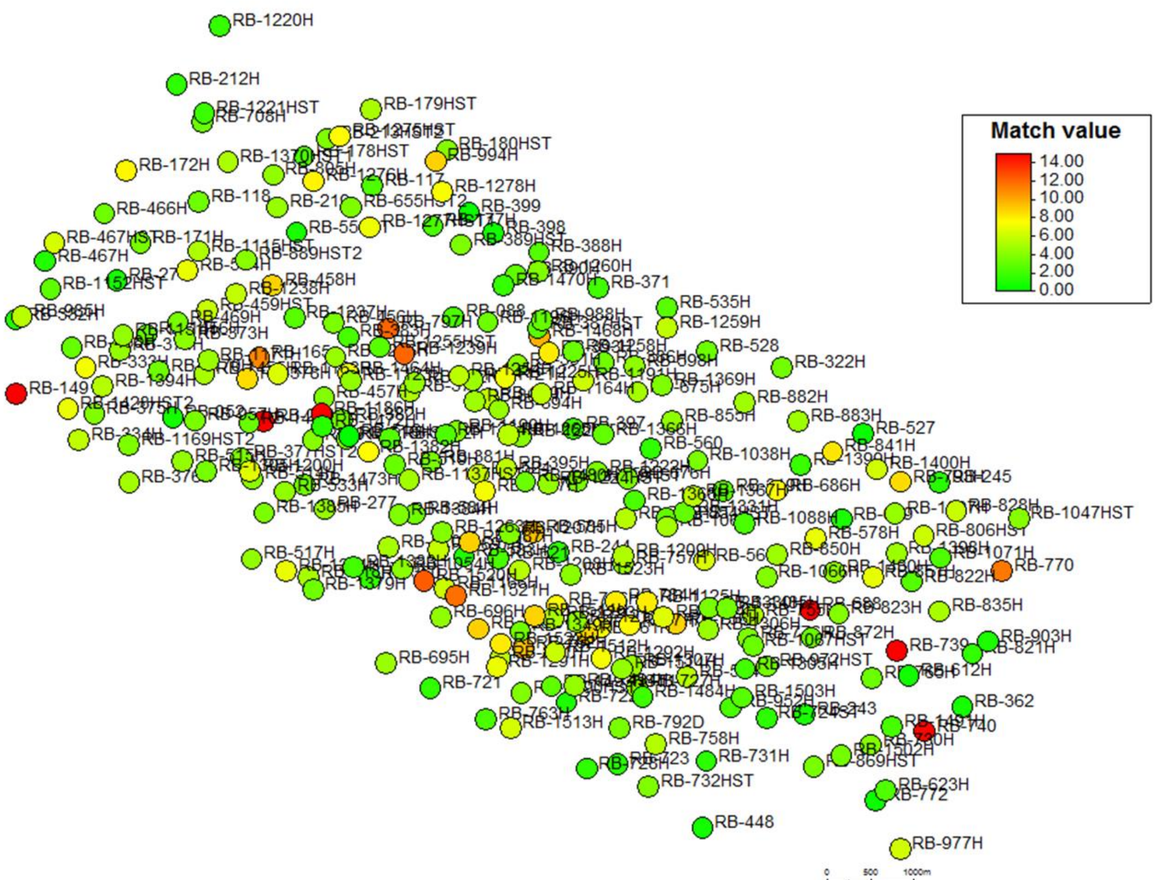

Figure 13. Mismatch map showing 80% of the wells (green) meeting history matching criteria on well level.

For other reservoir performance analyses, matched cases were used to extract data for validating results on well group level as well as zone level, shown in Figure 14, and by drilling campaigns, shown in Figure 15.

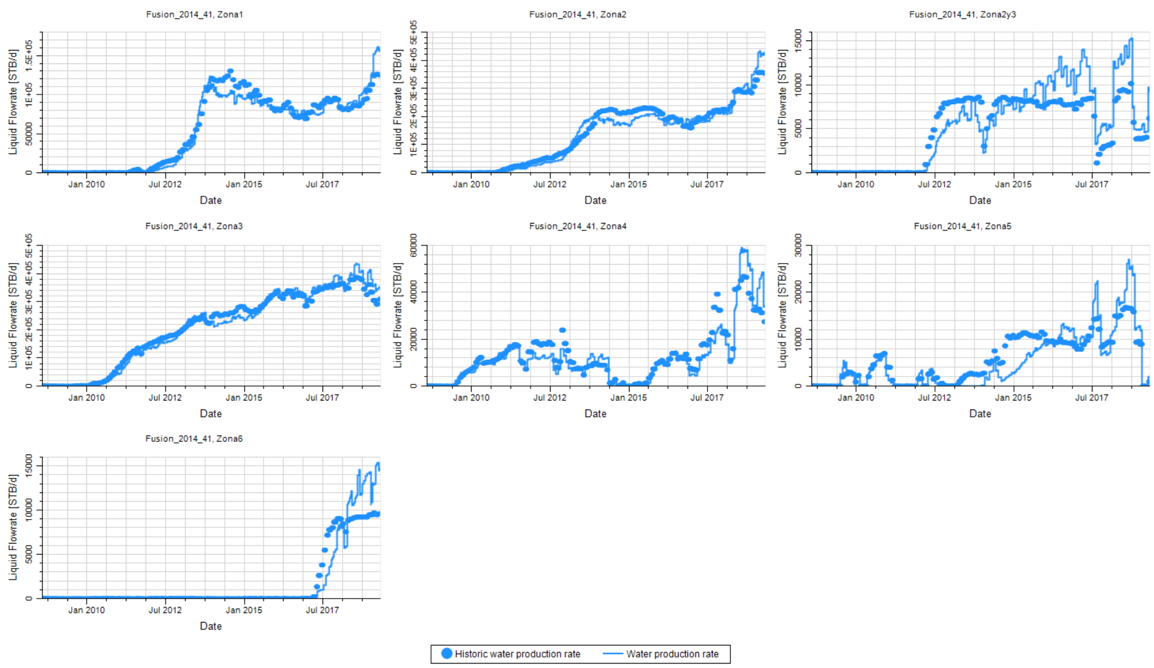

Figure 14. History match by zones

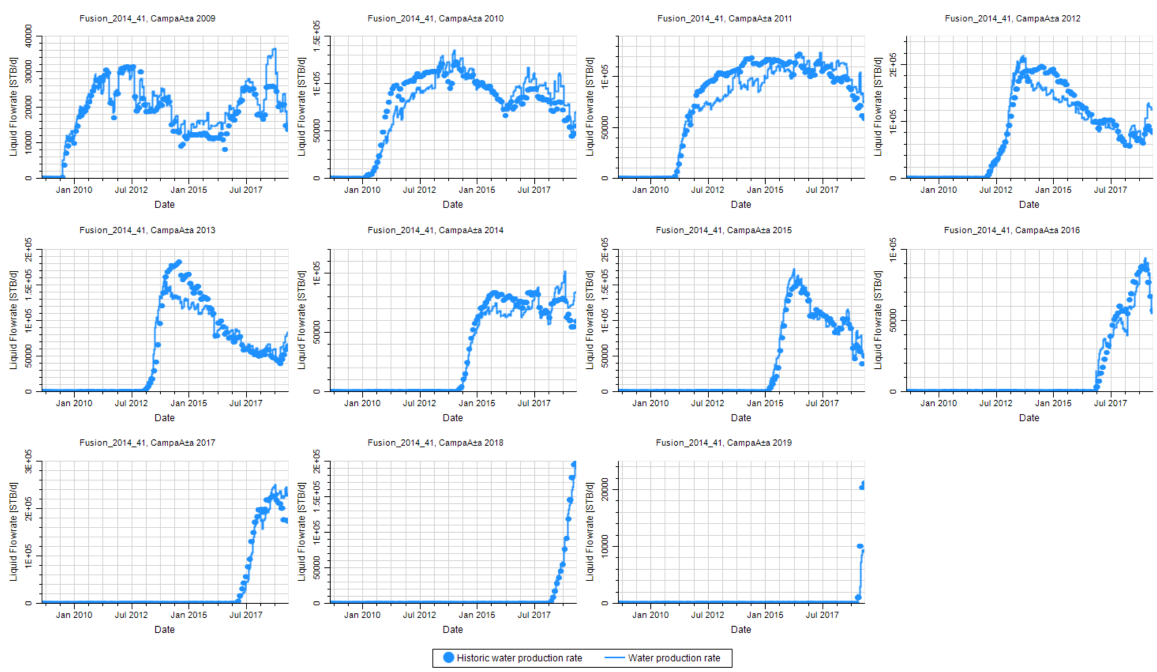

Figure 15. History match by Drilling campaigns

Figure 16 shows a direct comparison of historical to simulated results for cumulative well water production. Red triangles represent results for cumulative well water production drived from the base case model. Base case results show a broad spread of data away from the diagonal line which represents a perfect match. Green squares represent well results from the best case with a distribution close to the diagonal line which indicates a much higher match quality.

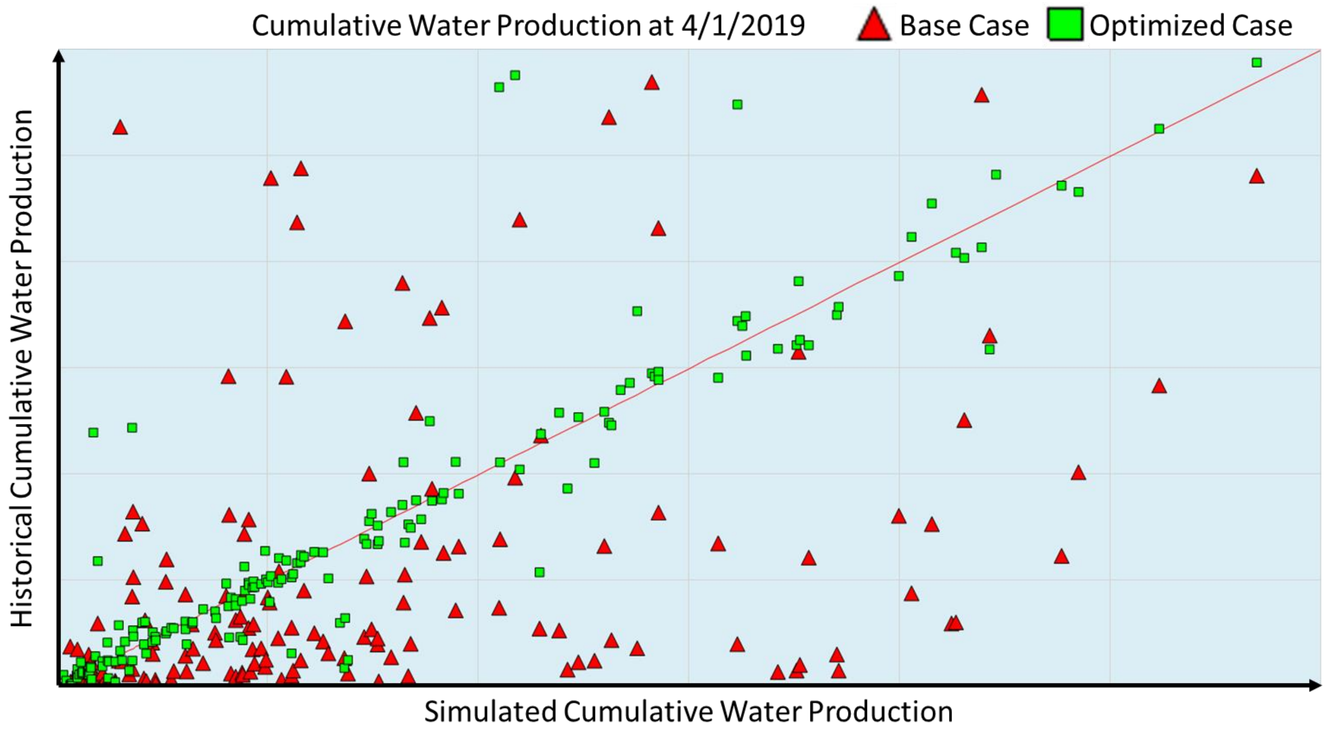

Figure 16. "One to one" graph of historical water production versus simulated model

Finally, Figure 17 documents the improvement of the history matching solution in a series of sequential update steps. The Y axis shows the ratio between simulated and historical production and the X axis shows the cases number. The base case shows a large ratio which indicates a poor match. At the end of the automated well-based optimization process, the ratio converges to values between 0.9 and 1.1 which represents a match within a 10 % error margin.

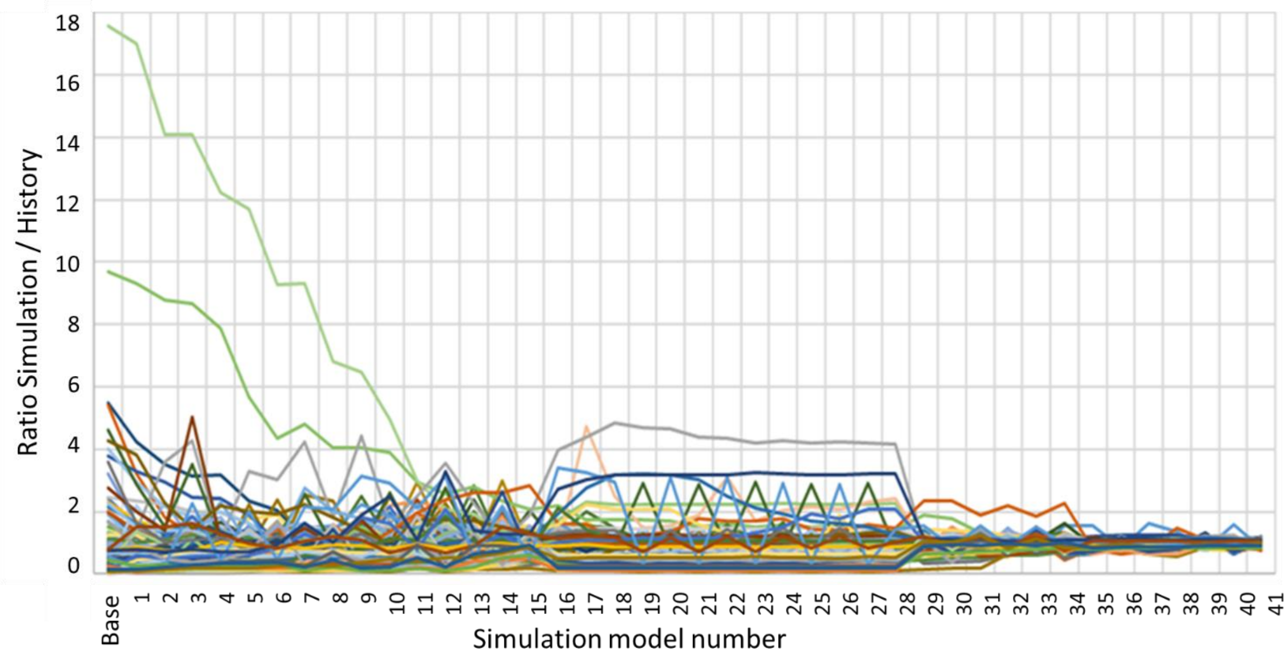

Figure 17. History match evolution

Other results in this phase are the final surface of the contact (Figure 18) and an example of the final distribution of rock types for the sealing zone below Zone 3 (Figure 19). The OWC surface has different depth areas that were modified to meet history matching objectives.

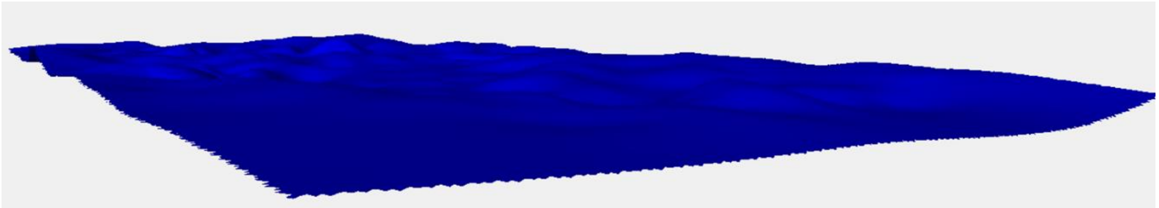

Figure 18. Final OWC Surface

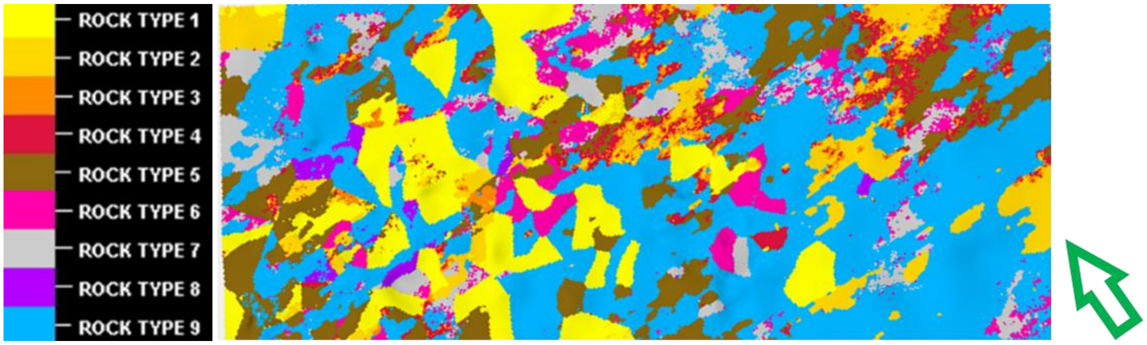

Figure 19. Final Rock type distribution for the seal bellow Zone 3

Water cut maps are an efficient method to quality control the history match. The comparison of historical to simulated water cut distributions was prepared for the 3 most important zones, which are shown in Figure 20. Image details show that the maps are similar, reaffirming once again the matching quality

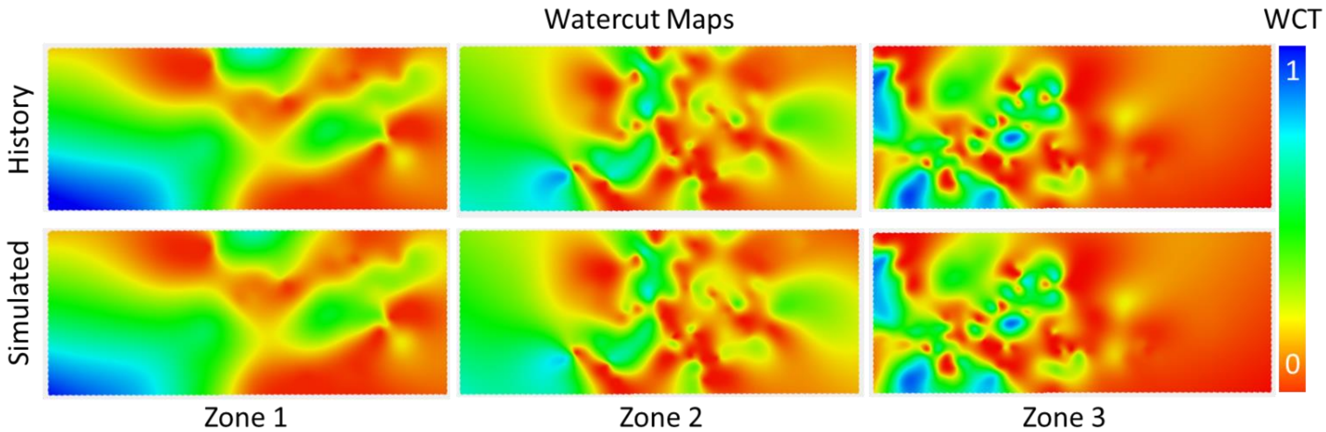

Figure 20. Water cut map for zone1, 2 and 3 for historical (upper row) and simulated data (lower row)

Another important indicator in the model calibration was the volume match, i.e., the production corresponding to all the matched and unmatched wells was grouped separately to quantify the volume percentage corresponding to each group. Figure 21 shows that the relative volume of water originating from matched wells is 86%, while unmatched wells deliver just a small fraction of 14% to the total volume.

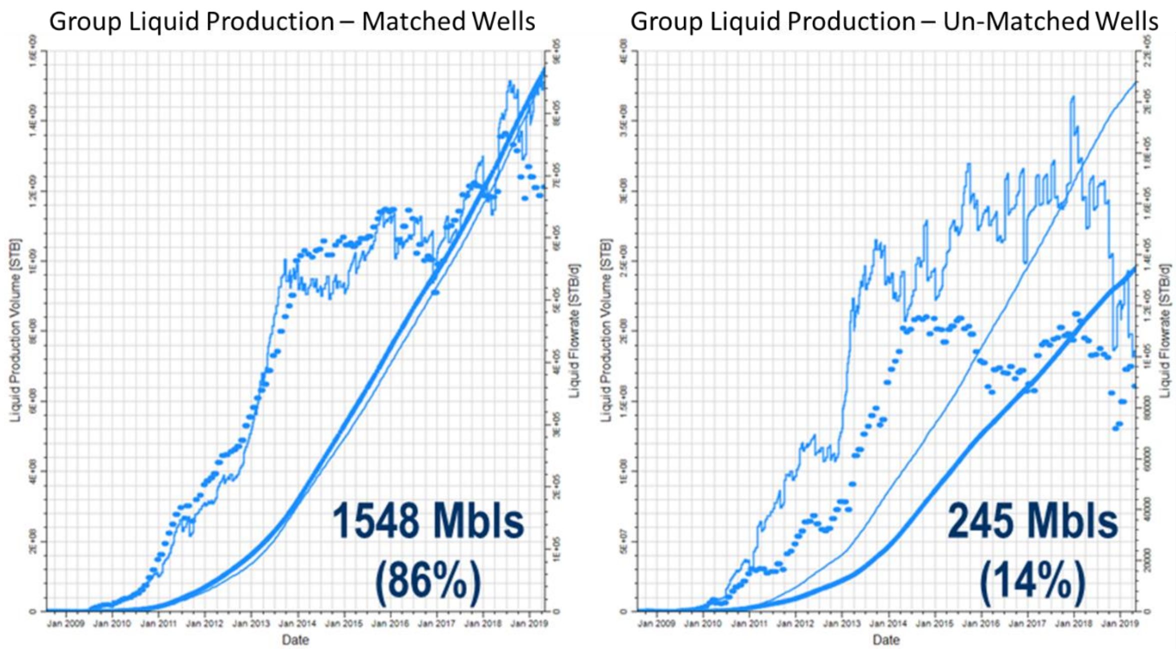

Figure 21. Percentage of liquid production volume for matched (left) and unmatched (right) group of wells

Finally, to verify the model predictability a blind test was carried out with 12 wells already drilled that were not part of the history match workflow. The response from these wells showed a mismatch of less than 20% (Figure 22), which is good enough to assume that the model is reliable.

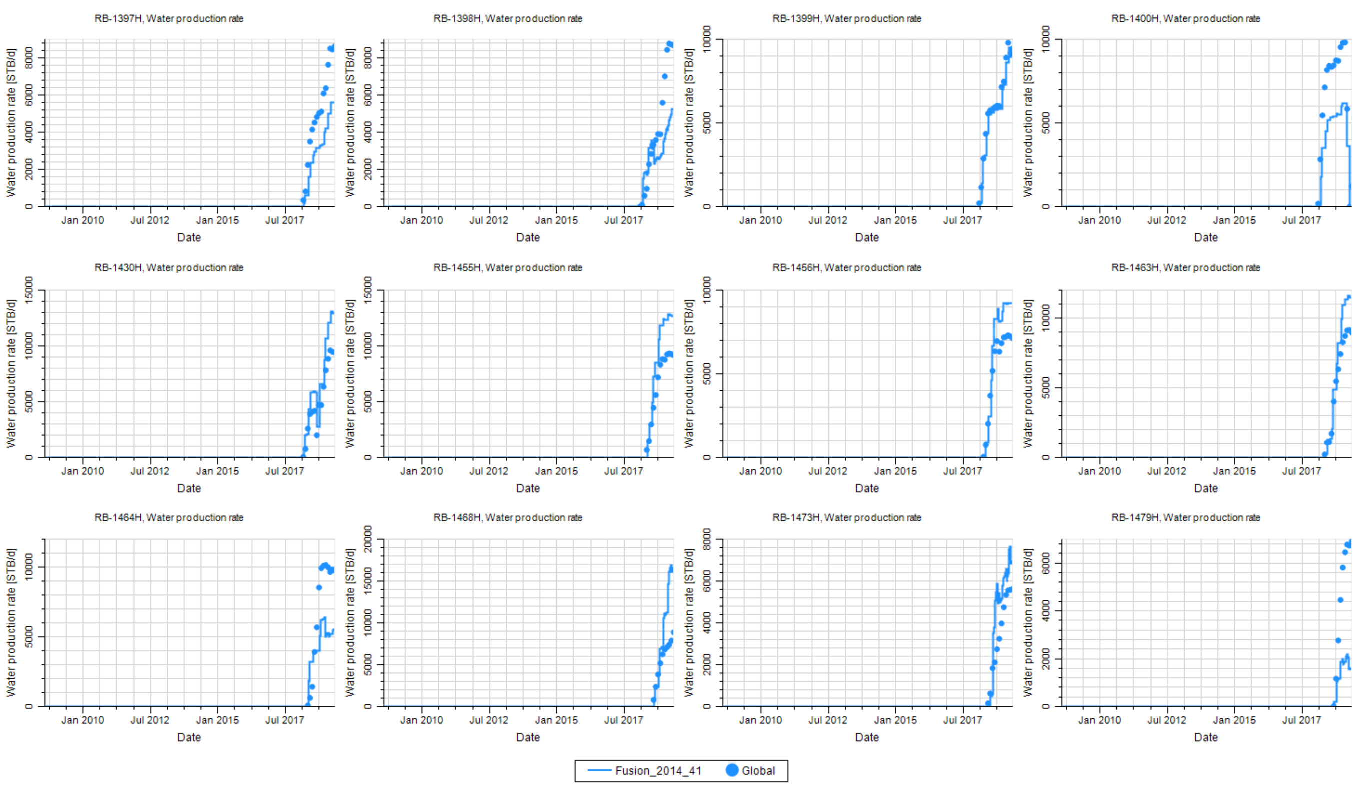

Figure 22. Blind Test for the last wells drilled in the sector

Production forecast

The original field development plan included a number of infill wells. An economic well performance indicator was used to evaluate the field development plan under uncertainty (Schulze-Riegert, and others, 2020a). Individual wells were investigated under the assumption that the well production needs to meet the economic demand of the well, i.e., the production revenue needs to justify capital and operational expenditures.

Economic success metric

A simplified economic model used for the Net Present Value (NPV) calculation as defined below:

$$NPV = \sum_{j=1}^{N_t} \frac{R(t_j) \cdot \Delta t_j}{(1+d)^{t_j/\tau}} \tag{1}$$

with the following contributions described in Table 1

$$R(t_j) = \left(Q_{op}(t_j) \cdot r_{op} - Q_{wp}(t_j) \cdot r_{wp}\right) - D(t_j) \tag{2}$$

Table 1: NPV parameters definition

Parameter	Description
$Q_{op}(t_j)$	Oil production volume
$Q_{wp}(t_j)$	Water production volume
r_{op}	Revenue (oil)
r_{wp}	OPEX (lifting, disposal)
$D(t_j)$	CAPEX Drilling
d	Discount factor
Δt_j	Time interval
N_t	Number of time steps

Regarding the input data for the NPV calculation is shown below:

1. For both, the deterministic and probabilistic economic well ranking, a distinction between oil and water production is mandatory.
2. Operating and lifting costs must be related to water production.
3. Royalties applied at the field or asset level are irrelevant for this type of analysis
4. Drilling and operational costs define a minimum economic volume for a well to be profitable. Economic input data included in the calculation is listed in Table 2

Table 2: Economic input data

Parameter	*Unit*
Oil price (r_{op})	USD/bbl oil
Lifting costs	USD/ bbl oil
OPEX water costs (r_{wp})	USD / bbl water
Royalties	%
Average Well Drilling costs $D(t_j)$, discounted and effective at production start	USD/producer
Discount factor	%

Drilling costs are connected to the well length (“Measured Depth), The following equations summarize the calculation.

The average length over all well candidates is defined by

$$\overline{MD} = \frac{1}{N} \sum_{i=1}^{N} MD_i \tag{3}$$

A weight factor is included to account for length

$$w_i = \frac{MD_i}{\overline{MD}} \tag{4}$$

Well drilling costs account for length

$$D_i = w_i \cdot D \tag{5}$$

Probabilistic assessment of infill well performance

As part of the well-by-well performance analysis, the following calculations are made: P10, P50, P90, standard deviation, minimum, maximum and probability of each well for delivering an NPV above a threshold value.

To evaluate different generic scenarios, several NPV thresholds were established (1 MUSD, 2 MUSD and 4 MUSD). Figure 23 shows an example for a well with a 4 MUSD target. In this example, the probability of success to deliver that economic objective is 58 %.

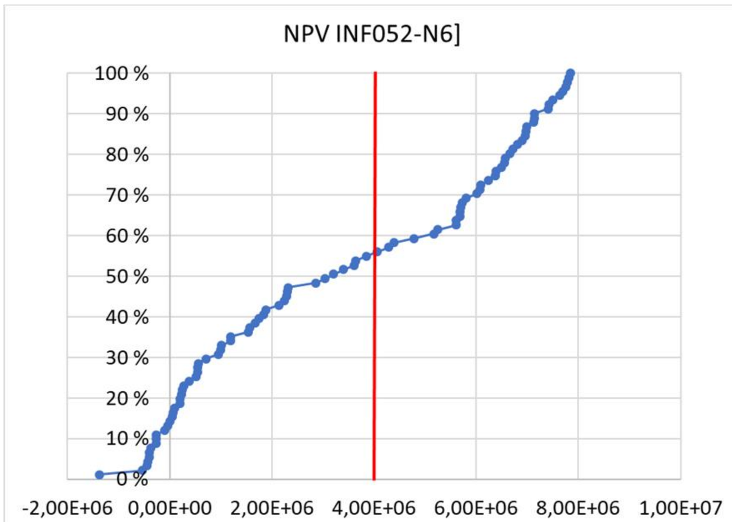

Figure 23. NPV cumulative distribution for well INF052-N6

Figure 24 shows a histogram for the well to deliver above the economic threshold of 2 USD million. In this case only 23 wells 90 to 100% chance to deliver above 2 USD million.

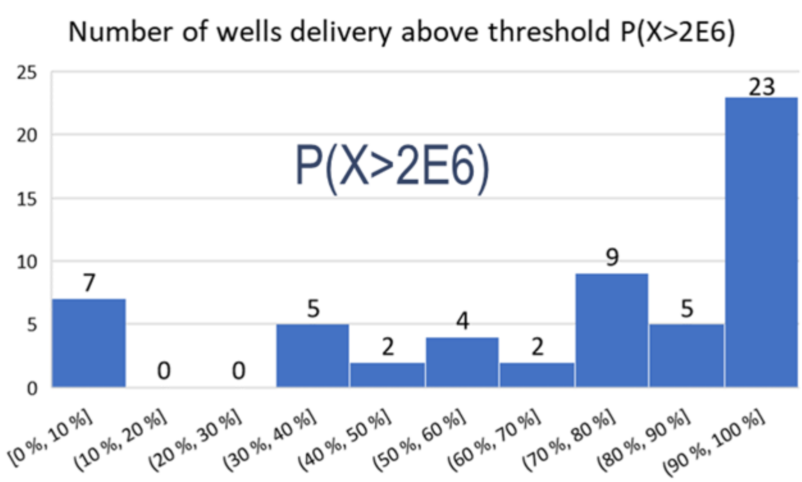

Figure 24. Success probability for wells able to deliver an NPV >= 2E6

This probabilistic assessment is extended to all wells, shown in Figure 25. More than 50 % of the total number of proposed wells are below the red line, i.e., they are not able to deliver above the economical demand. A well with a 58 % chance of success is highlighted (red circle) and the related NPV and cumulative oil profiles for the same well are shown in top right

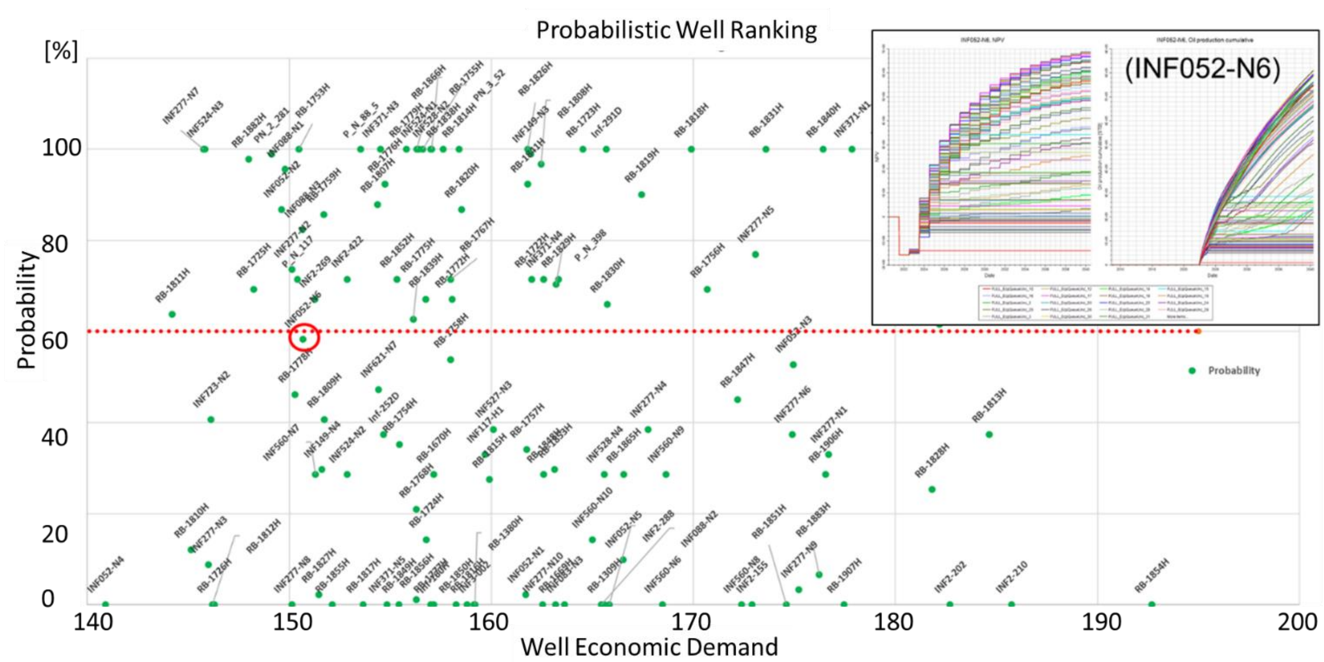

Figure 25. Probabilistic well ranking of all infill well candidates. The diagram shows the probability of a well (y-axis) to deliver least the economic demand of that well (x-axis, normalized scale). Profiles based on all matched cases are shown for well INF052-N6 (upper right) which has a probabilistic success rate of 58% to deliver the well economic demand (red circle).

The Figure 26 shows the histogram and the cumulative density function for one selected well candidate. Only 58 % of the cases were able to deliver an NPV value greater than its economic demand, which indicates a risk that the well will not mee the required economic performance.

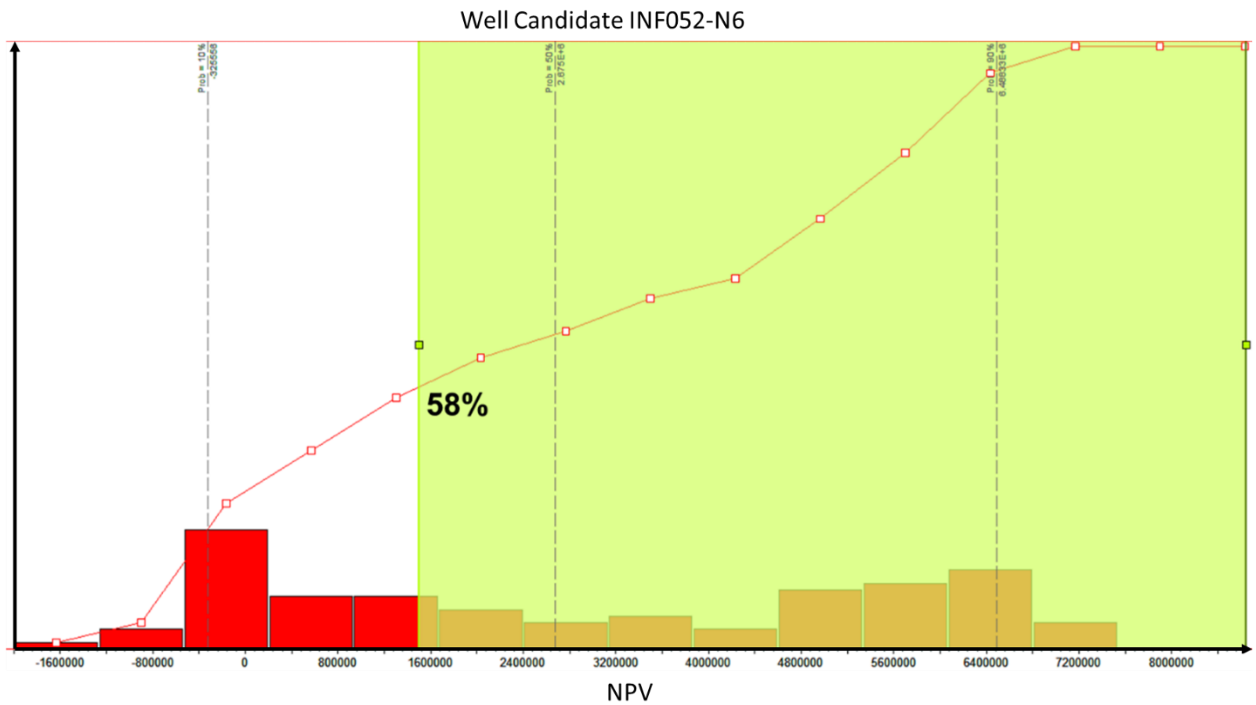

Figure 26. Probability density (histogram) and cumulative density function (red line) for the well candidate INF052-N6. For the well candidate 58% of all evaluated cases deliver the economic demand or higher (green shaded area).

Sweet spot map – Identify high performing wells.

Once the NPV analysis was completed in all the proposed wells, the simulation opportunity index, "SOI" was calculated, which is based on a paper and was slightly modified adapting it to the reality of the Rubiales reservoir drivers and embodied in an automated workflow that serves not only to locate new wells but also to validate the results of NPV vs SOI. For the calculation of the SOI, 4 sub-indexes were considered as described below:

ISO: Oil Saturation Index

$$ISO = \frac{(So - So_{min})}{(So_{max} - So_{min})}, \quad (6)$$

IHCVP: Hydrocarbon Pore Volume

$$IHCPV = \frac{(HCPV - HCPV_{min})}{(HCPV_{max} - HCPV_{min})} \quad (7)$$

IKH: Flow Capacity Index

$$IKH = \frac{(KH - KH_{min})}{(KH_{max} - KH_{min})} \quad (8)$$

IFWL: Free Water Level Index

$$IIFWL = \frac{(FWL - FWL_{min})}{(FWL_{max} - FWL_{min})} \quad (9)$$

These indexes are the dominant production drivers that are part of the next equation SOI: Simulation opportunity index

(10)

All calculations were implemented within a customized workflow for automated execution on a geomodelling platform (Schlumberger 2020). The automated workflow execution facilitates and speeds up the creation of this property for each of the 6 producing zones and it allows to generate the input values per well for creating the plot in Figure 27.

In order to validate this index as a good measure of the historical behavior and to consider it useful for future recommended new wells, a cross plot of SOI vs Cumulative Oil was done to all the wells drilled from 2008 to 2014 (Figure 27). From this cross plot it is clear that an SOI value greater than 0.33 gives a percentage of success of 96%.

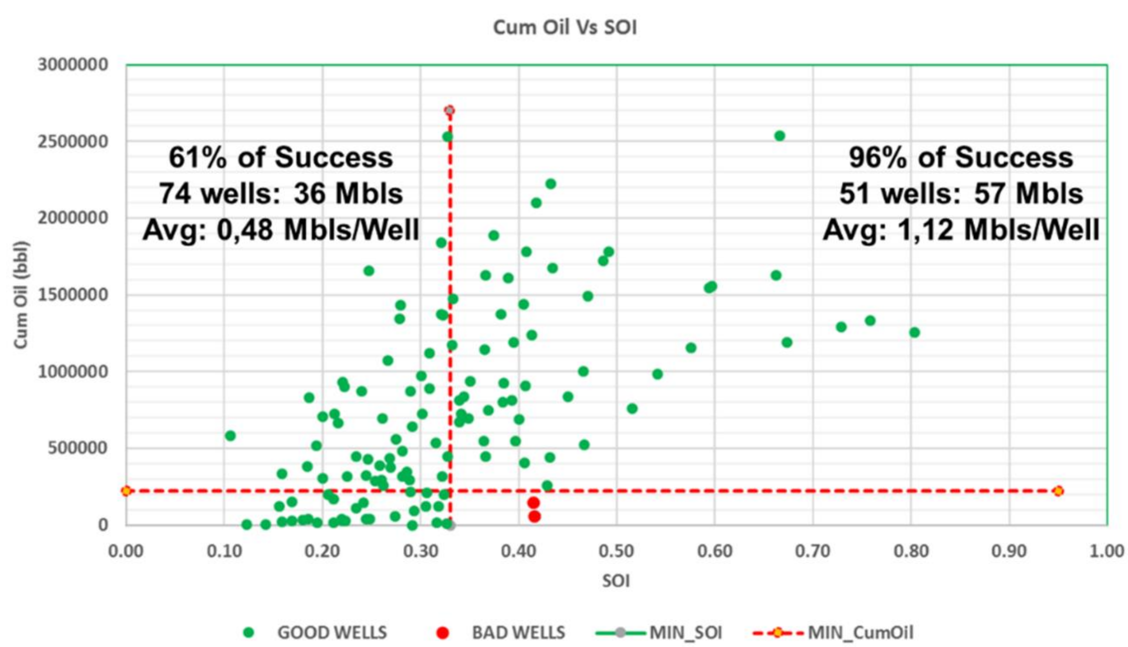

Figure 27. SOI vs NP

Additionally, in the Figure 28 the same graph is presented highlighting the abandoned wells. It can be seen, that only 16% of the abandoned wells have a SOI greater than 0.33. On the contrary, there is a higher probability that wells with an SOI of less than 0.33 will be abandoned. These two graphs are considered useful to establish this value as the appropriate cut-off for searching new wells targets in the study sector.

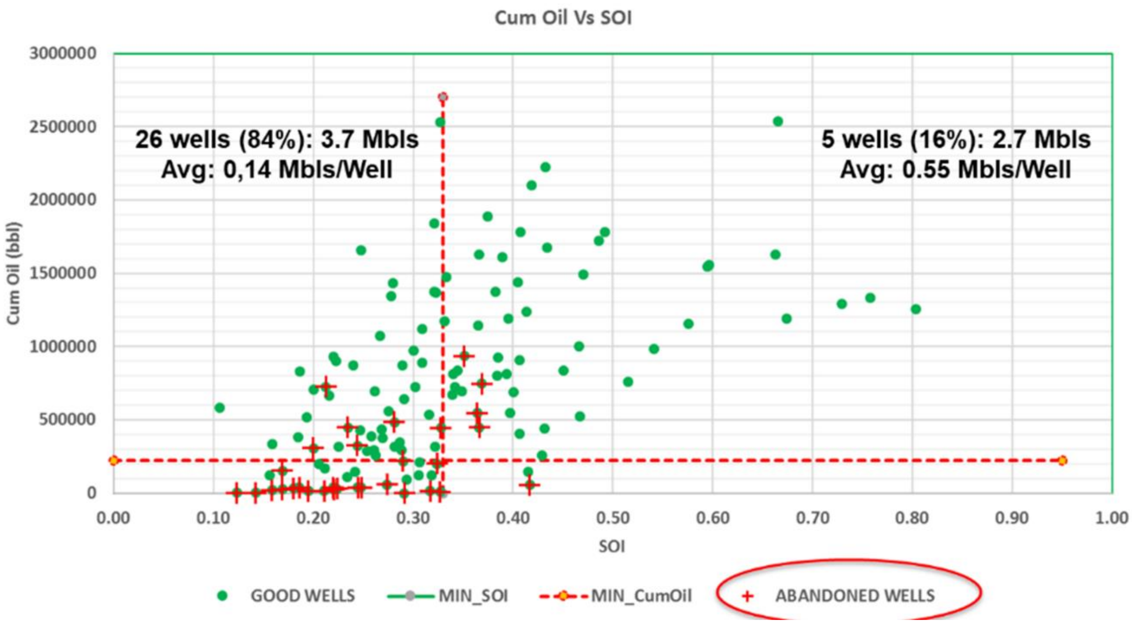

Figure 28. SOI vs NP with abandoned wells

Taking the previously detailed analysis as a reference, additional graphs of NPV vs SOI were made for the wells initially proposed, which reaffirms that the percentage of success is notably higher for values of SOI>0.33, Figure 29 shows the example for P50 scenario.

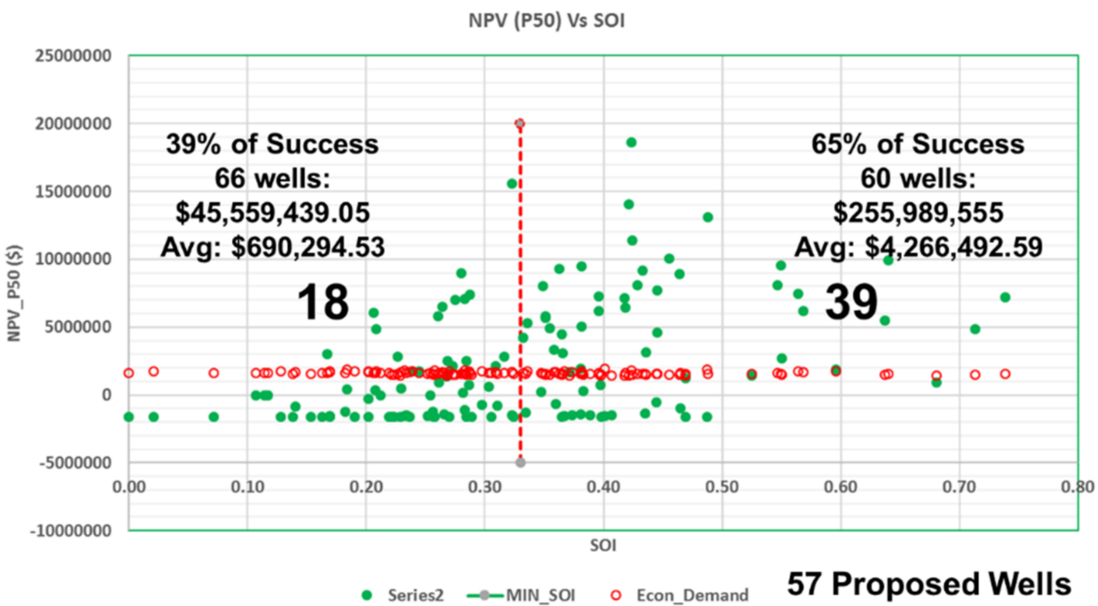

Figure 29. SOI vs NPV_P50 for the wells proposed initially

With these results, a final development strategy was created to run some additional prediction scenarios leaving out the riskiest wells, the forecast was run using P10, P50 and P90 matched cases, the results of these scenarios in terms of water and oil production (rates and accumulated) are shown in the Figure 30

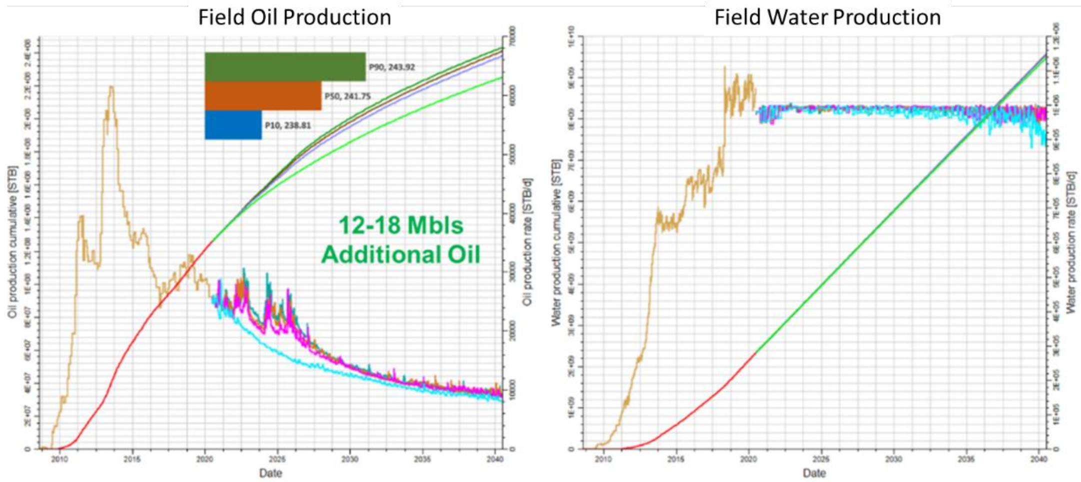

Figure 30. Field production forecast including the most productive wells proposed using 3 calibrated models

Once the proposed wells were evaluated and ranked, complementary scenarios were run with 32 additional wells proposed based on the SOI results. New sweet spots were identified for the FDP distributed in the reservoir zones shown in Figure 31

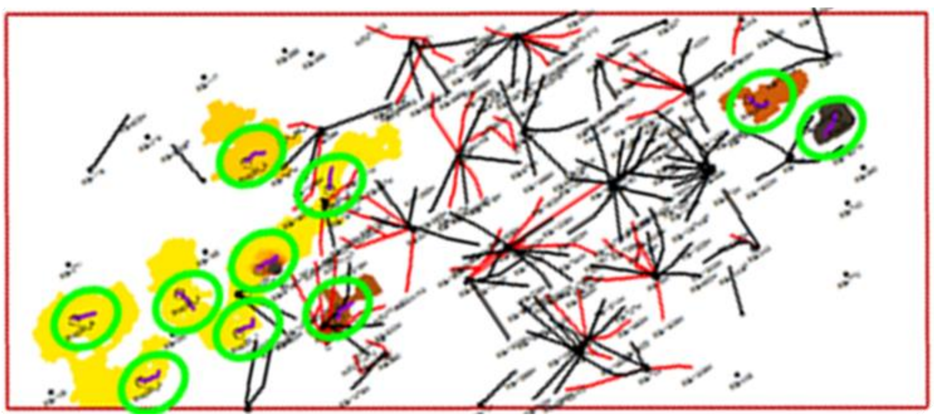

Figure 31. New targets (green circles) identified in Zone 2

A new production forecast including the most economic wells from the initial candidate list combined with 32 new locations, delivers an additional cumulative oil production of 24-30 Mbls with 39 fewer wells compared to the initial infill well candidate list, (Figure 32).

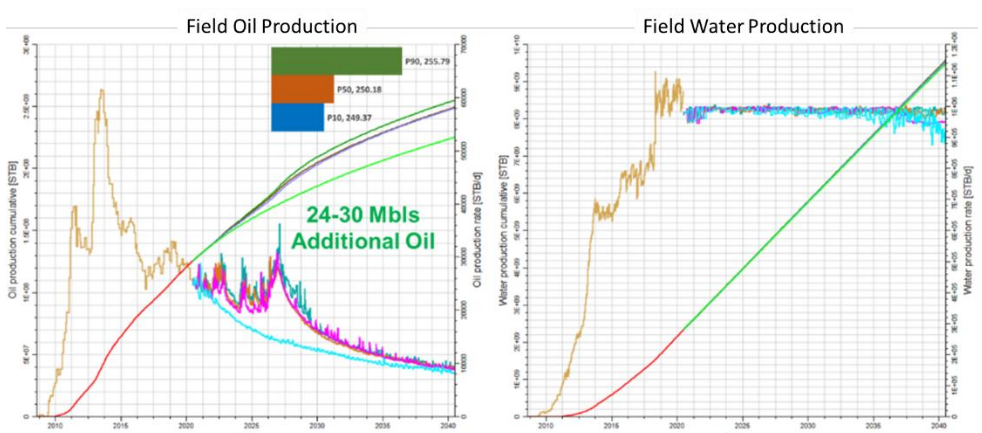

Figure 32. New forecast adding the new locations

The proposed well performance based on SOI targets demonstrated to be an effective way to locate wells with a high probability of success. Figure 33 shows well oil production cumulative for all wells. Only 1 out of 32 wells in total was not able to deliver the minimum economic demand.

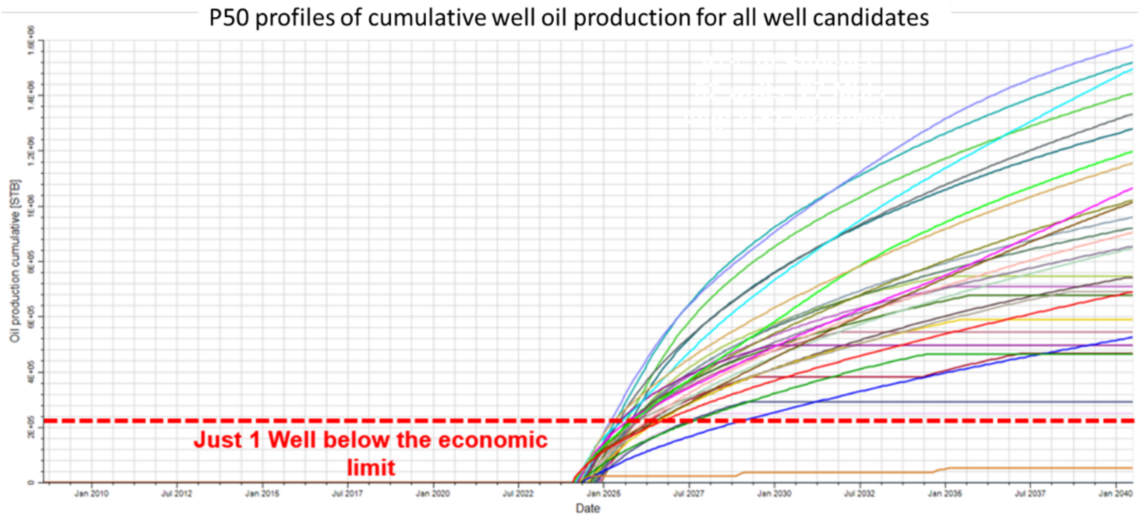

Figure 33. Well performance for the targets found with the SOI

Conclusions

A well-by-well based calibration workflow has been implemented and customized for different areas of the Rubiales field. The automated history matching execution time was significantly reduced compared to previous attempts. Within 30 simulation runs an 80% history match at well level was achieved. The fully automated sequential workflow design was executed within 120 hours or 5 days of total run time.

Integrated digital technologies provided informed insights to reservoir management of the Rubiales field considering operational well actions and field constraints.

Under the framework of Ecopetrol’s digital innovation framework called ‘accelerated field development plan (aFDP)’, functional workflows were created on a cloud computing platform for automated history matching and evaluation of prediction forecasting scenarios including production optimization under subsurface uncertainty with an estimated elapsed time of up to 70%.

Ensemble-based results were created for probabilistic evaluation of economic success criteria on a well-by-well level. A simulation opportunity index and well-based NPV calculations were used for probabilistic well ranking and identification of sweet spots for new infill well locations with a positive investment return on additional production volumes.

Future innovation efforts will focus on parallel execution designs with a stronger integration of predictive modelling steps using machine learning technologies.

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Acknowledgement

The authors of this paper would like to thank the management of Ecopetrol and Schlumberger for supporting this work. Conclusions and opinions stated in this paper are those of the authors and do not necessarily represent those of Ecopetrol or Schlumberger.