Multiscale Geostatistical History Matching

Multiscale Geostatistical History Matching using Block-DSS and Uncertainty Quantification

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Abstract This presentation proposes a way to speed-up the history matching and integrate the multi-scale character of reservoir models into the model update loops. The model update loop consist of optimization of a reservoir model on a coarse grid, and then performing history matching on a fine scale based on the large scale properties inferred from the coarse model. The proposed novel methodology couples different geological scales through geostatistical assimilation of the small scale geological features using Block Direct Sequential Co-Simulation and updating the large scale geological properties using Particle Swarm Optimization, in order to quantify the uncertainty. The uncertainty quantification is integrated in the two loops: (i) model in a very coarse reservoir grid; (ii) model in a fine reservoir grid. We show this novel approach in a challenging synthetic case study based on a fluvial environment.

Keywords History Matching, Block Direct Sequential Simulation; Geostatistical Modelling; Particle Swarm Optimization

Introduction

The oil and gas industry is a very challenging and complex industry. There is a huge uncertainty, a lot of different risks and considerably amount of money involved in the exploration and production of oil and gas. Generally, in a oil and gas project, the available information is mostly discrete, sparse and with different support volume and resolution: core measurement; well logs and seismic surveys and all of this increase the complexity in the financial project evaluation.

In reservoir modelling we try to describe the spatial distribution of the subsurface properties of interest by integrating all the available data: well-log data, seismic reflection, production data and geology. The geology of the reservoir is defined and this geological definition allows the characterization of different type of rocks: carbonates, shales and sand; different types of structural elements: faults, rollover, anticlines; the existence of channels and other different types of structures. It is also defined the petrophysical reservoir properties such as porosity, permeability and saturation and it is through this information that we are able to study and predict the fluid flows in the reservoir.

The more understanding we acquire about the reservoir's properties, the better the modelling and its characterization, leading to better decision making. It will be easier to define the number and the location of new wells, define the amount of existing oil and predict the economic return generated by the same. The reservoir modelling should represent, in a reliable way, the reservoir characteristics and should be processed within an acceptable period of time. The computers and the software have improved and developed deeply in the last years and now they allow data processing faster and more efficiently, however the amount of required and available information remains extremely high. The processing time reduction keeping the quality of the model is one of the industry challenges.

In a history matching problem, dynamic data is incorporated to model a reservoir, i.e., we model the geological reservoir properties conditioned to the known dynamic data. With this methodology we aim to model the internal reservoirs' properties, porosity and permeability, by perturbing the parameter model space in order to match the available production data.

Reservoir modelling conditioned to history matching consumes a lot of CPU time since we need to solve a fluid flow simulator at each iteration step. To optimize this procedure one solution is to modify the scale of the reservoir, upscaling it. This upscaling reduces the number of grid block and the number of unknown parameters allowing for faster fluid flow simulations but this upscaling take out important information, in particular, in the small scale heterogeneity. As a result, after obtaining an optimised coarse grid model is very important to refine it, conditioning the fine grid model to block and point data.

Different authors studied this problem and proposed some solutions. Lui & Journel (2009) developed an extension of the traditional DSS that is able to integrate data in different supports, Block-DSS and this is a reliable form of stochastic downscaling. Mata-Lima et al. (2007) developed a new inverse modelling methodology that is able to integrate dynamic data in a static model through the application of a geostatistical DSS tool. Aanonsen and Eydinov (2006) developed a multiscale technique that is characterized by physical models with multiple scales, in this case, different spatial scales. The matching of these scales is made using the data production history from each model.

We will combine all this knowledge to develop and implement a new stochastic tool, which allows us to build a high resolution model conditioned to the known data: well-log data and historical production data, faster and with accuracy.

In this project we also want to account the uncertainty in the parameters of multiscale geostatistical history matching. Through the generation of multiple history matched models we will be able to quantify the uncertainty and the probability of future production; we could also know what the most likely scenario is and what the respective confidence intervals are. Different authors studied this problem and proposed some solutions. There are several stochastic sampling algorithms that allow us to quantify this uncertainty: the Ant Colony Optimisation (Hajizadeh et al. 2009), the Particle Swarm Optimisation (Mohamed et al., 2009) algorithm and the Neighbourhood Algorithm (Christie et al., 2006) and all these algorithms are based in the Bayesian Theorem.

To sum up, the challenge of this paper is to build a 3D high resolution model conditioned to the known data: well-log data and historical production data, faster and with accuracy that takes into account the uncertainty on it.

The goal is to provide a new workflow and a software tool that is able to optimize this process and answer to this big challenge.

This paper proposes a new way to speed-up the history matching and integrates the multi-scale character of reservoir models into the model update loops. The model update loop consists of an optimization of a reservoir model on a coarse grid, and then performing history matching on a fine scale based on the large scale properties inferred from the coarse model. The proposed novel methodology couples different geological scales through geostatistical assimilation of the small scale geological features using Block Direct Sequential Simulation and updating the large scale geological properties using Particle Swarm Optimization, in order to quantify the uncertainty. The uncertainty quantification is integrated in the two loops: (i) model in a very coarse reservoir grid; (ii) model in a fine reservoir grid. We show this novel approach in a challenging synthetic case study based on a fluvial environment.

With the application of a downscaling algorithm we intended to get a fine grid model with high resolution and detailed information that integrates information from the coarse model and information from the data from the wells.

Methodology

This paper presents a new methodology for geostatistical history matching; multiscale geostatistical history matching that takes into account the uncertainty at multiple scales. We developed and implemented a new algorithm to speed-up the history matching on multiple-scales and then quantify the uncertainty on it.

The proposed methodology integrates two different workflows:

1. Multiscale Geostatistical History Matching, MSGHM – integrates two geostatistical history matching workflows at different scales;

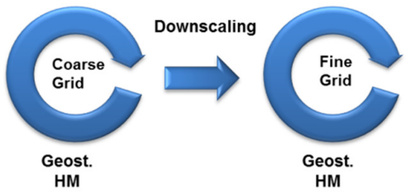


Figure 1 – Multiscale Geostatistical History Matching General Workflow

2. Uncertainty in Multiscale Geostatistical History Matching – integrates uncertainty quantification in both scale levels.

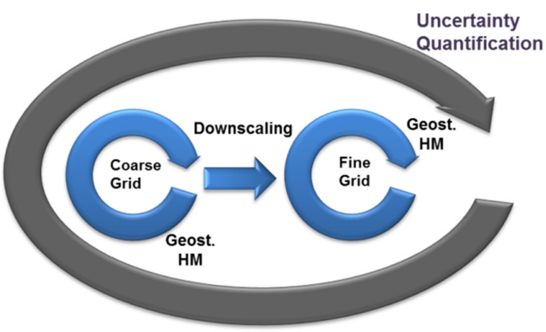


Figure 2 – Uncertainty in Multiscale Geostatistical History Matching General Workflow

The first workflow comprises a multiscale technique that is characterized by physical models on multiple scales, in this case, two different spatial scales. The proposed workflow integrates two geostatistical history matching loops: (i) model a very coarse reservoir grid; (ii) model a fine grid taking into account the coarse matched grid by integrating block kriging with direct sequential simulation, Block-DSS.

The second workflow integrates uncertainty quantification related with the geological parameters in the previous workflow. In this work we proposed to quantify the uncertainty in the spatial continuity related with the different geostatistical modelling scales of multiscale geostatistical history matching. This uncertainty quantification would be integrated recurring into stochastic adaptive sampling and Bayesian inference in both scale levels: fine grid and coarse grid.

Mutilscale Geostatistical History Matching

The aim of the multiscale modelling is to obtain an efficient and accurate approximation to the solution in the fine scale, high resolution model. The advantage of implementing multiscales parameterizations techniques is to use fast update of coarse models to constrain the history matching models in fine-scale. With this methodology a significantly reduction in processing time is obtained so it guarantees a faster and more efficient estimation that generates more consistent models. The procedure promotes a good integration of dynamic data in the static model and it ensures that the matching is retained through the downscaling step. The proposed geostatistical history matching algorithm comprises a multiscale technique that is characterized by physical models on multiple scales, in this case, two different spatial scales.

To apply MSGHM the following steps should be done:

1. Collect prior information: well-log data, production data and spatial continuity, from a synthetic reservoir model. The production data will be used as a reference in the misfit.
2. Run a traditional geostatistical history matching:
    a. Create a set of equiprobable images from a reservoir property with a stochastic DSS tool;

b. Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;
c. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;
d. Create a perturbation in the initial image with the information obtained from the objective function and repeats all the previous steps until a minimum value to the objective function is achieved;

3. A best coarse grid reservoir model is achieved;
4. Run a downscaling geostatistical history matching - the best coarse grid model will be refined using a Block-DSS to downscale the matched coarse grid:
   a. Compute the block-to-block average, $\bar{C}_{BB'}$, block-to-point average, $\bar{C}_{BP}$, point-to-block average, $\bar{C}_{PB}$, and point-to-point, $C_{PP'}$, local covariance matrix;
   b. Create a set of equiprobable images from a reservoir property with a stochastic DSS tool;
   c. Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;
   d. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;
5. A best fine grid reservoir model is achieved.

This proposed methodology is represented in the previous detailed framework (Figure 3).

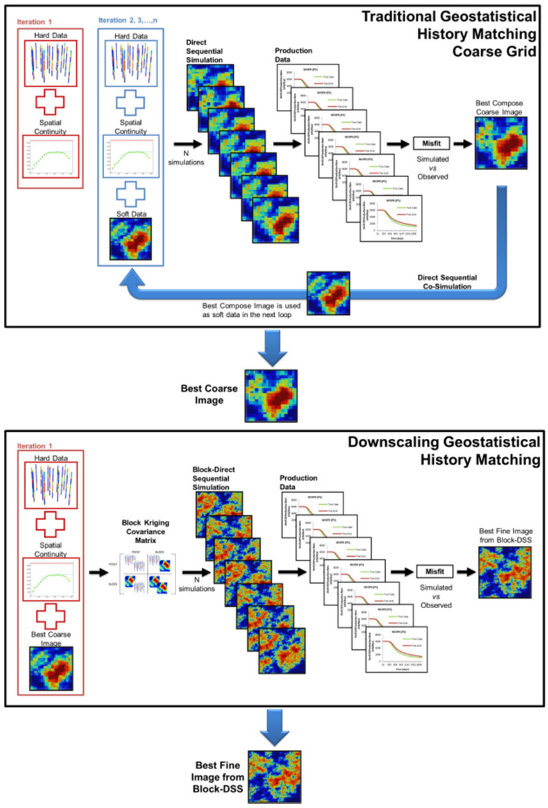


Figure 3 – Multiscale Geostatistical History Matching Detailed Workflow

Uncertainty Quantification

The previous workflow of MSGHM assumes stationarity in the geological parameters but in a true case there is a huge lake of information about the parameters and therefore a lot of uncertainty. This uncertainty in the geological parameters can be related with the spatial continuity, as variograms, and with the properties distributions, as the mean and the standard deviation.

In this work we proposed to quantify the uncertainty in the spatial continuity related with the different geostatistical modelling scales of MSGHM, thus we will have uncertainty in the large scale correlation, small scale heterogeneity and in the downscaling procedure. This uncertainty quantification would be integrated recurring into stochastic adaptive sampling and Bayesian inference in both scale levels: fine grid and coarse grid.

The methodology applied in this workflow is the PSO and it aims to find the best particle, represented by the set of the 5 parameters that are responsible to define the spatial continuity in the model. The spatial continuity is defined by the variograms, the range and the angle, as a result, instead of using a fix value for the range and the angle, a uniform distribution is assumed. This change will be implanted in the MSGHM and the simulated model will allow the uncertainty quantification in the reservoir.

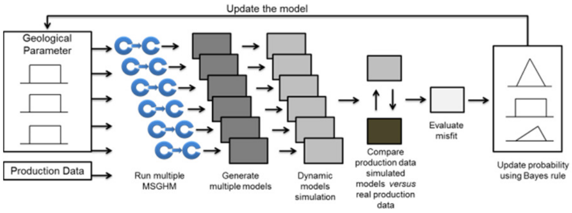


Figure 4 – Multiscale Geostatistical History Matching Uncertainty Quantification Framework

Case Study

The 3D synthetic reservoir represents a fluvial system with 1km (North-South), 1km (East-West) and 100m thickness dimensions. The fine grid is defined by 160 000 blocks discretized by [100x100x16] cells with 10mx10mx6.25 each.

<u>*Mutilscale Geostatistical History Matching*</u>

The traditional geostatistical history matching in the coarse grid run 30 iterations with 10 simulations each in 1h47m. The best-fit inverse model (Figure 40 and 41) was able to reproduce the spatial distribution of the main channels without great detail. This model was then used as conditioning data in Block-DSS for the history matching at a much finer grid (Figure 42).

The downscaling geostatistical history matching runs 15 iterations, in 1h34m. The results from the fine grid do not represent the shape of each individual channel but the trend is very well illustrated (Figure 43). Notice that for the fine grid we only need to run 15 iterations to reach a good match. This is a crucial improvement when compared with the traditional geostatistical history matching that would need much more iterations and consequently more execution time. As in the coarse grid simulation, also in the fine grid there is an improvement in the spatial distribution with the increase of the number of iterations.

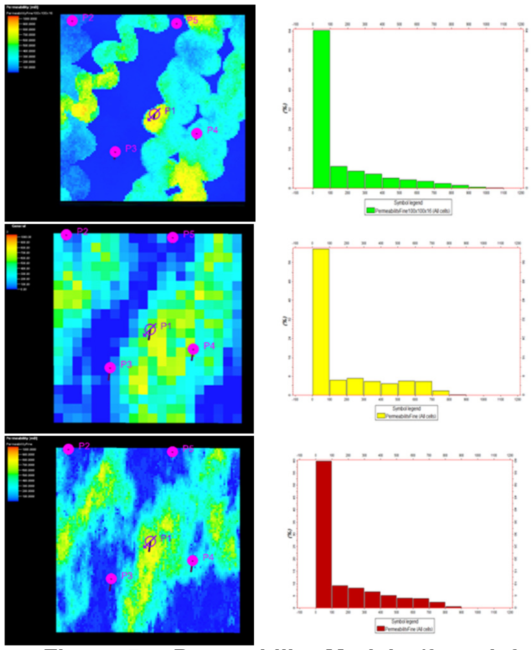


Figure 5 – Permeability Models (from left to right, top to down): a) Reference Model b) Histogram from Reference Model, c) Best Coarse Model, Iteration 30 (Matched Realization), d) Histogram from Best Coarse Model, Iteration 30, e) Best Fine Model from Block-DSS, Iteration 7 (Matched Realization), f) Histogram from Best Fine Model from Block-DSS, Iteration 7

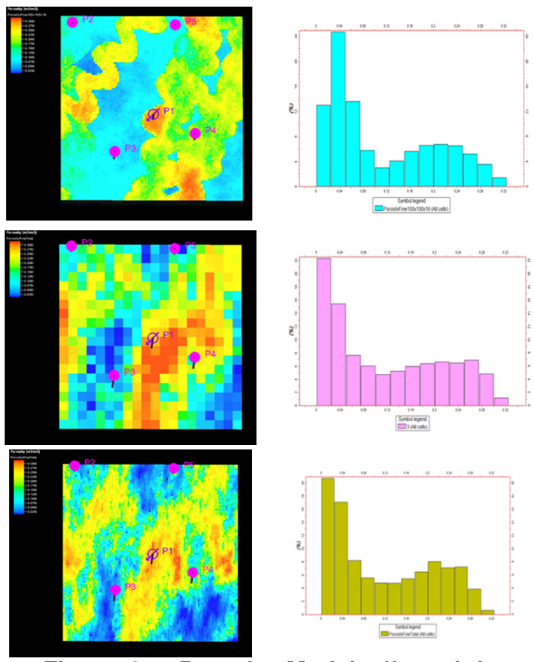


Figure 6 – Porosity Models (from left to right, top to down):: a) Reference Model b) Histogram from Reference Model, c) Best Coarse Model, Iteration 30 (Matched Realization), d) Histogram from Best Coarse Model, Iteration 30, e) Best Fine Model from Block-DSS, Iteration 7 (Matched Realization), f) Histogram from Best Fine Model from Block-DSS, Iteration 7

Uncertainty Quantification

The previous workflow was implemented and tested assuming stationarity in the parameters but in a true case there is a huge lake of information about the parameters and therefore a lot of uncertainty. To try to quantify this uncertainty, the previous methodology was implemented and tested taking into account the uncertainty in the parameters, in this specific case the uncertainty in the spatial continuity of the data in the both scale levels: fine grid and coarse grid.

We studied 2 level of uncertainty. In the coarse grid we quantified the uncertainty in the kriging and variogram, represented by their angles and ranges. In the fine grid we also quantified the uncertainty in the kriging and variogram, represented by their angles and ranges and the error in the downscaling kriging step.

Table 1 - Uncertainty Quantification: Parameters and Prior Distributions

Parameter		Prior Distribution	Range
Spatial Continuity	Range XX		[75, 90]
	Range YY		[50, 150]
			[400, 100]
	Angle		[200, 600]
Downscaling	Error		[0.1, 0.5]

To quantify the uncertainty in the model spatial continuity we run 150 iterations, simulating 5 models of porosity and permeability per iteration. At each iteration we updated the ranges and angles from the variogram in X direction and Y direction. The methodology was implemented until day 1000.

The production data from the simulated reservoir models match considerably well the production data from the synthetic model. We can see that PSO has modelled a range of models that fit reasonably the observed history data.

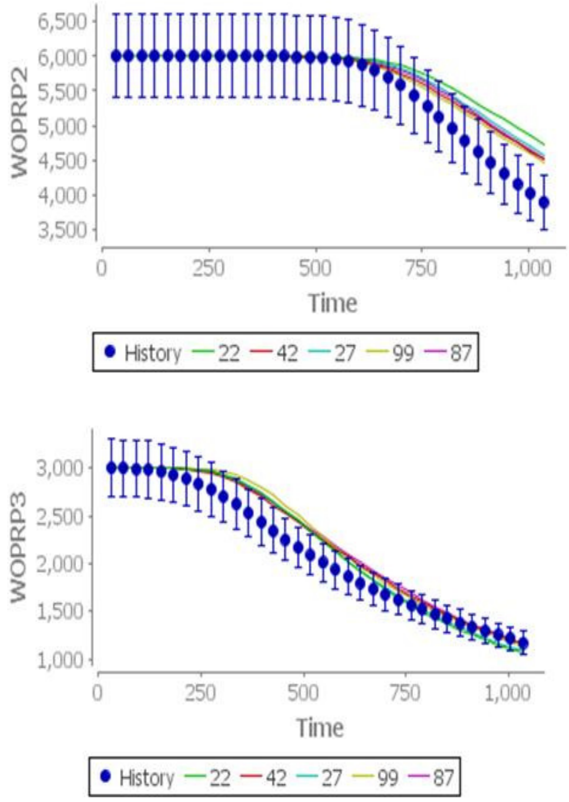
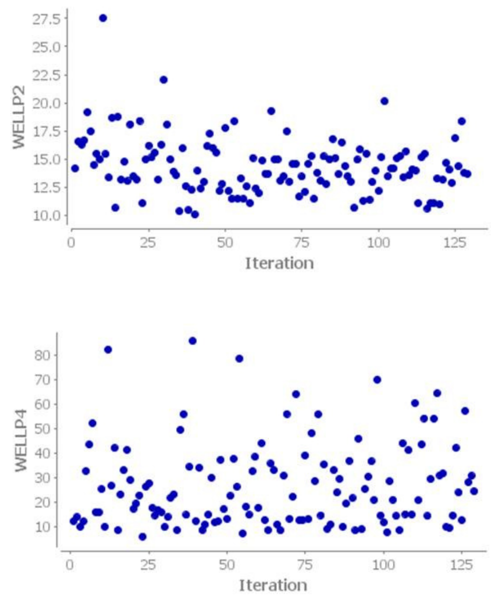


Figure 7 – Best History Matching from PSO: a) Well Oil Production Rate Well P2, b) Well Oil Production Rate Well P3

The figure plots the best misfit obtained in each generation of the algorithm versus the generation number. The misfit is showed per Well P2, P4 and P5. With only 150 iterations it is very difficult to see a trend and a misfit convergence.



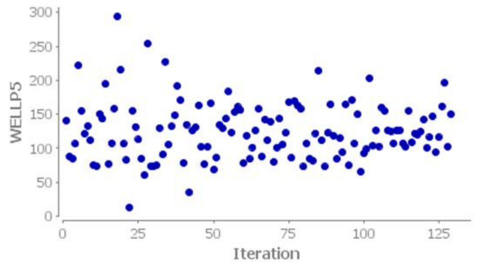


Figure 8 – PSO Misfit Evolution per Well

The Figure 9 shows the evolution of the space parameter per misfit. This misfit was studied per well and in the figure we can see the evolution of the Y direction range parameter in well P3, the evolution of the X direction range parameter in well P5 and the evolution of the parameter angle in well P2. As the number of iterations increase the misfit decrease and we start to see a convergence to a value, reducing the range of possible parameter values. In well P2 the angle tends to converge to a range angle between 85.0 and 90.0.

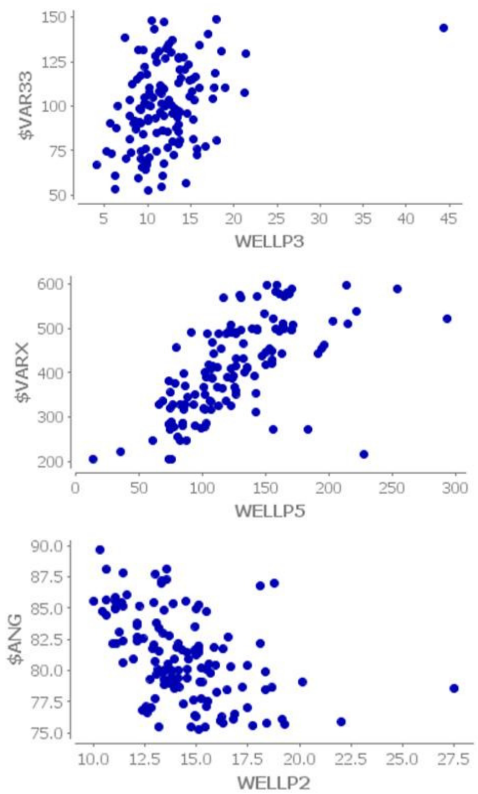


Figure 9 – Parameter versus Misfit

Conclusions

The presented methodology demonstrated to have high potential. The proposed algorithms are able to be implemented in a 3D model, are easy to use and modify and are practical.
The application of this novel multi-scale geostatistical history matching methodology presents the following advantages:

- Reduces the overparameterization problem in the fluid flow equations;
- Faster assimilation of large scale corrections into history matching;
- The coarse geological model is retained through the downscaling step, providing a better initial model for the final adjustment on the fine scale.
- The downscaling allows us to characterize the small scale heterogeneity in the fine grid reservoir model and history match it;
- Substantial reduction in the HM CPU time – best coarse reservoir in 1500 simulations (11h) and best fine reservoir in 55 simulations (15h);
- Both results from the fine grid and the coarse grid are consistent with the reference model geology;
- The best-fit model is able to reproduce the spatial distribution of the main channels;
- Generation of models with different resolutions but all with good matching history;
- The space of uncertainty is reduced and can be assessed, by generating multiple history matched models

The results of this study ensure that simulated models honour the data points and the block data from the available experimental data; reproduce the statistics, probability distribution and joint-probability distribution; and the spatial continuity pattern imposed by the variograms. In general this workflow is very promising since the results from the coarse grid and from the fine grid are consistent with the

reference model. The majors patterns are reproduced, however it is difficult to represent reservoir models with complex structures, as channels and meanders. The iterative optimization assures the match between the dynamic responses from simulated models and historical production data.
With the implementation of this methodology we are able to simulate models with high resolution conditioned with low resolution models. The solution is a fast algorithm able to model a 3D reservoir in a reasonable time.

It is difficult to represent reservoir models with complex structures, as channels and meanders so to achieve good results with this kind of reservoir others workflows can be integrated on it.
As a background workflow we can integrate a seismic inversion framework. The implementation of seismic inversion as part of the history matching procedure allows to model a reservoir with a few wells or wells at sparse locations and to use the geological information to model the complex morphology and the distribution of the petrophysical properties.
As a forward workflow the study of the connectivity of the channels can be done. Sometimes in reservoir with complex structures, as channels, is difficult to achieve a convergence in the dynamic responses because a small change in the shape of the channels, for example in the width or in the thicknesses could make a huge change in the connectivity of the channels and therefore in the production data. To optimize this procedure we can study the connectivity of the channels to try to predict paths and patterns and optimize the reservoir modelling.
In the uncertainty quantification the study was made only to the spatial continuity. It was only taken into account the uncertainty in the parameter related to the spatial continuity in both scale levels, but there are a lot of different parameters with uncertainty in these workflows that can be quantified. Encouraging results with this workflow are obtained and in the future this should be applied in real reservoir studies from various different fields

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