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Multi-Variant Selection from History Matching to Prediction in Probabilistic Dynamic Model: A Case Study

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Abstract
Multiple history matching approach to quantify remaining oil saturation distribution uncertainty is possible and practical to perform with technological advancement nowadays. This paper presents the selection method to optimize number of forecast variants while preserving the uncertainty. The results are low estimate, best estimate and high estimate of remaining oil saturation distribution for development scenario design and wide-covered representative variants to be used for prediction stage.

Different model variants considered match with historical data are selected based on few criteria such as field total liquid production, field total oil production, region pressure and well total oil production. To be able to measure how similar or different one variant to another, cluster analysis was performed. The clustering was based on significant parameters to objective function which were used to build proxy-equations. In this study, Multi-Dimensional Scaling (MDS) method was used to visualize the result in two-dimensional space. Each variant represented by a point and the distance between points show their degree of similarity. After grouping process finished, different remaining oil saturation distribution were analyzed from P90, P50 and P10 quantile models.

There were 400 variants on final history match stage and then 127 variants were selected based on production and pressure profile similarity. Subsequently, number of forecast variants were optimized to 20 representative variants which cover the range of uncertainty. Three quantiles were selected from cumulative distribution function of these variants to be used for subsurface risk management in designing infill well location or waterflood pattern.

This paper demonstrates the application of extended uncertainty analysis by combining static modelling to dynamic simulation uncertainty variables in Limau Barat Limau Tengah Field which applicable in most development fields. Assisted history matching algorithm used in this study were determined for full field simulation. This paper also introduces the application of probabilistic remaining mobile oil saturation maps in assessing subsurface risk for better decision making in field development.

Introduction
Oil and gas are known as high risk and high gain industry with charateristic of capital-intensive and require advanced technology. It is very difficult and expensive to measure or understand condition in subsurface where hydrocarbon accumulated in magnitude of hundreds or thousands of metres below the surface. Common practice to manage the risk is reservoir modelling which representing the physical features of subsurface condition. Data are gathered and analyzed to be able to mimic historical production and pressure data. Having done this, the reservoir model is used to predict production performance under different scenario. In case of successful development, the reward could bear this high-risk industry while in case of undesirable surprise, expected profit is certainly shrinking. Nowadays, easy-oil become harder to get and more uncertainty in finding and producing hydrocarbon. This unforeseen result actually could be quantified and managed for a better decision.

Popular tool to calculate hydrocarbon volume and predict recoverable reserves are reservoir modeling and simulation. Although static reservoir modelling has been applying probabilistic approach for the last decades, the dynamic reservoir modelling part is still using deterministic approach. As a result, single static reservoir model realization is selected for history matching which provides deterministic remaining oil saturation map to be analyzed for designing development scenario. It's a common practice, that single recovery factor per scenario is used to make business decision out of many possibilities. A significant discrepancy between field development plan and actual reservoir performance occur under this limitation.

Probabilistic approach in reservoir simulation
Capturing the other possibilities of remaining oil saturation distribution map is the main objective of applying probabilistic approach for the reservoir simulation. Having analyzed the potential risk and reward, decision makers could anticipate the worst and best possible outcomes and most importantly eliminate surprises. By assessing the risk, management could reduce the reservoir performance uncertainty by gathering new key data that contribute to uncertainty or consider to proceed with development plan.

Probabilistic approach change the way team work into more blended and synergy among interdisciplinary team. More discussion between geoscientist and reservoir engineer to design uncertainty parameters and their range. Tolerable history matching acceptance criteria prevent unrealistic model modification which has no geological sense. Over fitting in history matching process is unnecessary since historical data which become the reference also have uncertainty. Geoscientist could access the progress of history matching result and evaluate the impact of static uncertainty parameters to quality of mismatch.

Reservoir simulation run time become faster and faster, especially with technology advancement nowadays. This opens the opportunity to analyze fine-scale reservoir model or different realization of reservoir model efficiently (Darmawan, 2021). Combined with methodology and algorithm that effectively perform sensitivity and optimization, full-field probabilistic study become feasible and practical. Experimental design is a process to perform sensitivity study with few popular algorithms such as; Latin Hypercube, Tornado, Monte Carlo, Placket-Burman and Box-Behnken. Visualization of big data plays an important role to effectively analyze results and get insight from it. For example, tornado diagram visualizes single parameter variation impact while others are kept at base value while Pareto chart visualizes combination parameter variation impact compare to pre-determined objective functions. Further, mismatch between historical produciton and simulations could be minimized by applying Optimization. Example of optimization algorithms are such as; Particle Swarm Optimization, Differential Evolution and Ensemble.

Field application

This study applied probabilistic approach for history matching and prediction of Limau Barat Limau Tengah field and a first-step effort to integrate static-dynamic uncertainty variables. The field is located onshore in South Sumatra Basin. Depositional environment of the field is fluvio-deltaic with updated geological concept, multi-level reservoirs. Waterflood development will be challenge with the new geological concept, so there are 9 reservoir tanks are prioritized for further development out of 20 reservoir tanks. Production commenced in 1951 and water injection started in 1998. There are 160 wells in total, 80 producing wells, mostly commingled production. Fluid characteristic from the field is 25^{o}API with no gas cap found in the studied tanks. The total original oil in place from 20 tank reservoir is 291.2 MMSTB (P50) with cumulative oil total 45.9 MMSTB per 1st January 2020 and water cut above 94%.

Purpose of this study is to perform probabilistic reservoir simulation for better understanding of the field. Output from this study are different scenario of remaining oil saturation distribution map for risk assessment and optimized number of multi-variant model to be carry out to prediction stage.

Method

A workflow was built to manage probabilistic history matching and prediction for Limau Barat Limau Tengah field as shown in **Figure 1**. Pre-defined static model variations were imported to be integrated with dynamic model uncertainty. Additionally, PVT correlation input data were included as uncertainty to cover laboratory measurement inconsistency. When the reservoir has been characterized in dynamic modeling format, reservoir simulation was performed until match criteria fulfilled. Preparation prior to prediction stage were history match variants selection and development scenario pattern design.

Integrate static-dynamic uncertainty variable and range

Existing probabilistic static model that has been built by geoscientists were imported, excluding its water saturation model. Water saturation model were not imported from the existing static model due to an update applied in this study using J-function approach. The 3D geomodel consists of 7.7 million total cells with dimension 219 x 212 x 156 and block size 50 m x 50 m x 1.4 m. There wasn't upscaling process performed since active cells was only 0.66 million cells. The reservoir properties were rebuilt to be included in uncertainty design for history matching. There were 37 static modelling variables such as variogram parameters for properties distribution and OWC. The reservoir properties are facies (or lithology), porosity and NTG. These variables were then combined with dynamic simulation uncertainty variables such as rock properties, PVT and aquifer properties. Following this, dynamic uncertainty variables and range were determined. The static modelling and the dynamic simulation processes were calculated in a common workflow to automate the multi-realization cases.

Fluid properties and rock properties data obtained from laboratory measurement such as SCAL, RCAL and PVT were analyzed. Flow zone indicator (FZI) technique was applied for rock type classification and later the classification was used to correlate porosity-permeability for each rock type. Relative permeability and capillary pressure data from few samples were normalized and then de-normalized for each rock type. PVT samples were inconsistent each other, possibly due to acquisition time was not at initial condition. It was decided to use correlation with parameter input of oil API and bubble point pressure and gas gravity. The first two parameters were included as uncertainty variable. Existing material balance analysis was used for initial parameter setting of aquifer model and its uncertainty. Subsequently, they were inputted to the integrated modeling software tool including well-related data such as historical well-based production and injection data, field and tank pressure, equilibration data and perforation event.

Manage probabilistic initialization and history matching

Initialization of the integrated probabilistic static model with base case dynamic model has purpose to distribute pressure and saturation for each cell in initial condition. At this stage, calculated OOIP was obtained and then compared with volumetric OOIP from static model. Few methods available for initialization the dynamic model such as; equilibrium, equilibrium+SWATINIT, mix and enumeration method. This probabilistic study was using Equilbrium+SWATINIT method to avoid capillary pressure manual adjustment. After the reservoir was characterized, initialized and equilibrium-validated, probabilistic initial full run without any model modification were ready to perform prior to history matching.

History matching was performed with liquid control, subsequently oil and water profiles were tried to match for both field and well level. Assisted history matching algorithm such as experimental design and optimization were used to manage probabilistic history matching efficiently. Experimental design outputs were sensitivity of single and combination variables. For this study, Tornado experiment was run once and then followed by Latin Hypercube experiment iterations. Tornado diagram and Pareto chart were used to visualize significant parameters compare to objective functions. Prior uncertainty variables and ranges were updated based on this evaluation until historical profile and simulation are overlaid within acceptable range. Further history match was run by Optimization which has pre-determined objective function such as minimizing oil field mismatch and oil well mismatch. In this study, Particle Swarm Optimization (PSO) algorithm was selected to find several local solutions and global solutions. The method is applicable for many uncertain variables and to avoid being trapped at local solution (Kathrada, 2009). Each PSO experiment contained 400 variants which gave result of Pareto chart. The chart was used to screen and rank uncertainty parameter for the following experiment iteration. To determine when experiment has reached optimum result, Pareto front analysis was used.

Manage multi-variant reservoir model for prediction
Pre-defined acceptable match criteria were used for equiprobable history matching variants selection. The criteria were field liquid total and oil total tolerance, qualitative acceptable objective functions and qualitative tank pressure. Afterwards, there are two preparations for transitioning from history matching to prediction stage. First, optimizing number of variant to be carry out to prediction with representative uncertainty range. Another preparation is development scenario design based on few selected remaining hydrocarbon maps. In this study, MDS method was choosen for clusterization analysis which used *k-means* algorithm (Steinhaus 1956, Lloyd 1982). This algorithm minimizes the sum of square error between the points of clusters and their centers. MDS method visualizes how close the model variants are in terms of values of the selected parameters. Validation of this method was tried at smaller model prior to application in Limau Barat Limau Tengah field. Prediction performance of case with and without clusterization were compared as shown in **Figure 2**. Range of oil and water total profiles were similar although variant number have reduced from 89 to 12 models (87%). These selected history matching variants were carried over to prediction stage after the development scenario design was analyzed.

Manage subsurface risk
Cumulative Distribution Function of total oil parameter were established in order to select its P90, P50 and P10 for high, mid and low case determination, respectively. Two-dimensional map of Mobile Oil Per Unit area (NTG*SOIL*PORO*DZ) were established for each representative as subsurface risk assessment in designing development scenario. Risk and reward assessment applied to prioritize development for reservoir tanks. These selected 9 reservoir tanks combined have OOIP and oil cumulative production more than 80% of the whole reservoir tanks. Reservoir tanks with high OOIP and low recovery factor (RF) were suitable for infill primary recovery candidate prior to waterflood secondary recovery. Prediction runs were performed for selected history matching variants from January 2020 to January 2036. Waterflood preparation was estimated ready on January 2026, afterwards full-scale waterflood activity started with pre-defined constraints such as well liquid rate limit, well injection rate limit, botom hole pressure limit for injector, produced water re-injection, group liquid rate limit and economic limit for each well.

Result and Discussion
Static-dynamic model integration
Results of this study are presented from integrating static-dynamic uncertainty to managing multi-variant model run. In collaboration with all subsurface team, initial uncertainty parameters were drafted such as; porosity distribution, contact depth, NTG, facies, permeability multiplier, Kv/Kh multiplier, relative permeability, aquifer properties and fault transmissibiliy. Probabilistic static and dynamic model were recorded within common workflow tool. Afterwards, the probabilistic models were initialized which gave OOIP at 281.7 MMSTB, 289.7 MMSTB and 297.7 MMSTB for P90, P50 and P10 respectively. While volumetric OOIP from static model were 278 MMSTB, 283 MMSTB and 294 MMSTB.

Probabilistic history matching
Initial full run was exercised with liquid control with running time around 75 minutes. Liquid profile from simulation was far from historical data due to over optimistic water profile simulation model as shown in **Figure 3**. Based on this initial performance, dynamic uncertainty variables and range were determined in more detail prior to history matching process. Experimental design was performed with Tornado, Latin Hypercube and Optimization experiment iteratively. There were 400 runs for each iteration to match liquid, pressure, oil and water profile. Pareto chart showed residual oil saturation, aquifer, relative permeability and porosity distribution were the most significant parameters to variable oil field total. Another analysis with Pareto front as shwon in **Figure 4** indicated that further optimization experiment iteration would only give similar result, which means this experiment iteration has reached optimum result of multi-objective functions.

Transitioning from history matching to prediction
Selecting 400 variants to be carried over to prediction required quantitative and qualitative selection techniques as shown in **Figure 5**. The first step was to select probabilistic history matching from the last experiment. These variants were selected based on field liquid total mismatch tolerance 5% and oil total mismatch tolerance 10%. Qualitatively, acceptable objective functions oil wells mismatch < 650 and oil field mismatch < 3 were chosen. Regional or tank level selection was applied only for the tank pressure parameter. Variants with flat tank pressure profile were not selected, which reduced the output to 127 variants for the equiprobable history matching. The following step was variant clusterization to avoid similar variants selection. Assumption was made by taking 20 cluster to represent equiprobable history match variants as shown in **Figure 6**. In this study, the amount has considered sufficient to cover the uncertainty range and also practical to perform within half-day. These unique history matching variants were carried over to prediction stage when development scenario design was finished.

Subsurface risk assessment
OOIP after history matching process were 283.6 MMSTB (P90), 291.2 MMSTB (P50) and 307.4 MMSTB (P10). Compared to before history matching case, OOIP difference were less than 4% and the updated uncertainty range was shifted due to water saturation cut-off elimination. Few wells with perforation at transition zone could only produce sufficient liquid by doing this modification. Recovery factor range with corresponding cumulative oil production were 15.7% to 16.5%. Probabilistic history matching have reduced parameter's uncertainty-range during initial and final history match.

This study considered sufficient and practical to analyze 3 representative maps out of 20 maps for subsurface risk assessment. The P90, P50 and P10 quantile of cumulative oil CDF were determined. The more cumulative oil produced means the less remaining oil in reservoir, therefore low-side MOPU map originated from P10 cumulative oil case. High, medium and low case of MOPU map for 9 prioritized tanks were established and analyzed as shown partially in **Figure 7**. Having examined the risk, the low-side MOPU map was used for waterflood pattern design. Then, adjusted the pattern to actual condition which have considered surface, well and subsurface factors. Prediction of waterflood scenario was applied to 20 selected variants. The range of results represent static and dynamic input data uncertainties and also risk and reward of all variant model possibilities. Different performance behavior among variants could be analyzed for risk assessment as shown in **Figure 8**. Low case prediction variants in the red circle have key uncertainty parameters such as fluid contact at S Tank 1, aquifer properties and rock properties that drive the reservoir performance. These are focus area of data gathering in the future to reduce reservoir performance uncertainty. Suggestion for future work is focusing on cluster optimization. Optimum number of clusters could be evaluated and then applied to MOPU map for development scenario design.

Conclusions

❖ Hardware and software advancement nowadays could handle full field probabilistic simulation

❖ Automatic capillary pressure adjustment enable probabilistic initialization handling in effective and efficient way

❖ Clustering technique optimizes the number of model variants carried over from history matching to prediction

❖ Subsurface risk was assessed by evaluating multi-variant MOPU maps for development scenario design

❖ Probabilistic approach could suggest key reservoir performance uncertainty drivers which are valuable insight for business decision making

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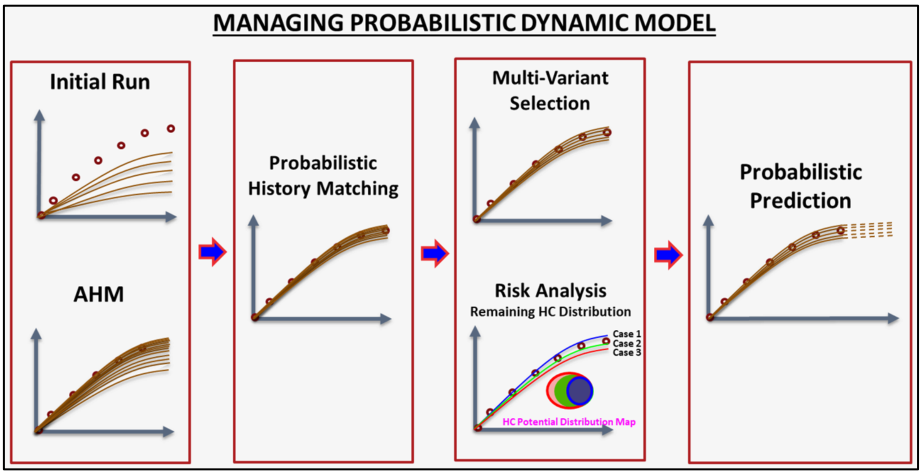
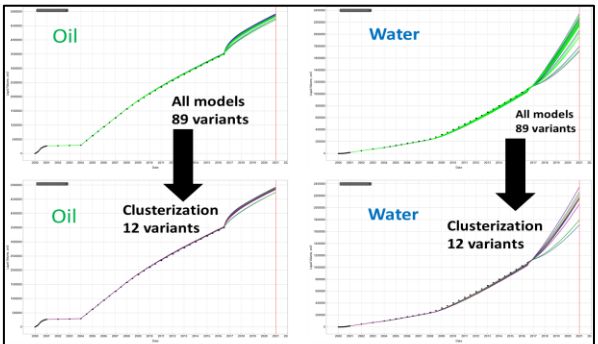


Figure 1. Probabilistic Dynamic Model Workflow



Method	# variants	Np P90	Np P50	Np P10
All models	89	4.744 MMSTB	4.859 MMSTB	4.926 MMSTB
MDS Clusterization	12	4.743 MMSTB	4.874 MMSTB	4.919 MMSTB
Difference	87 %	0.02 %	0.31 %	0.14 %

Figure 2. MDS clusterization validation

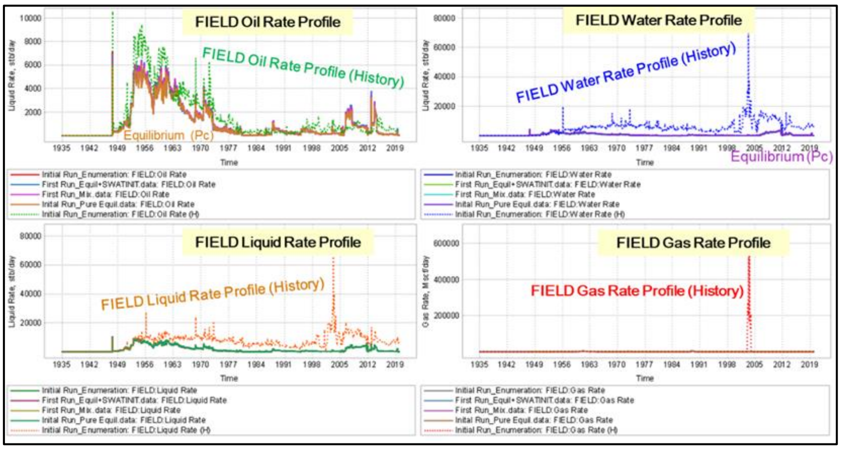


Figure 3. Initial full run

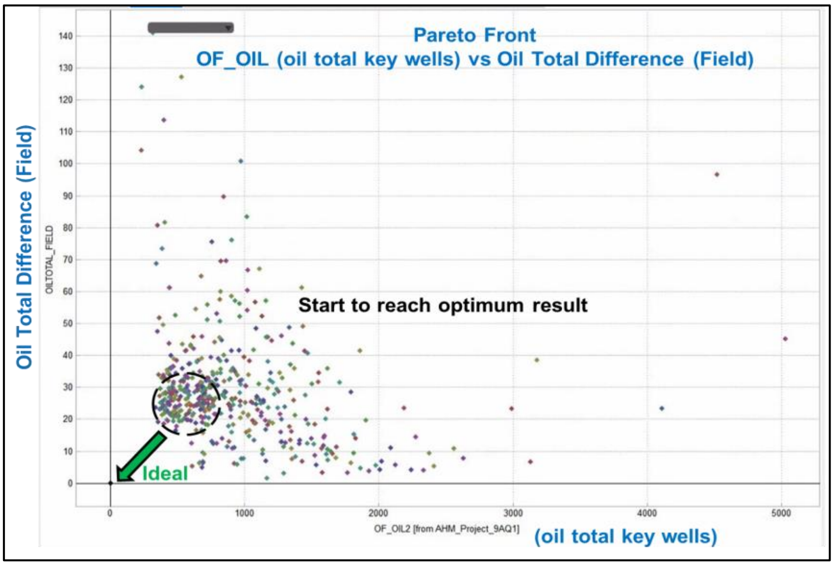


Figure 4. Pareto front analysis

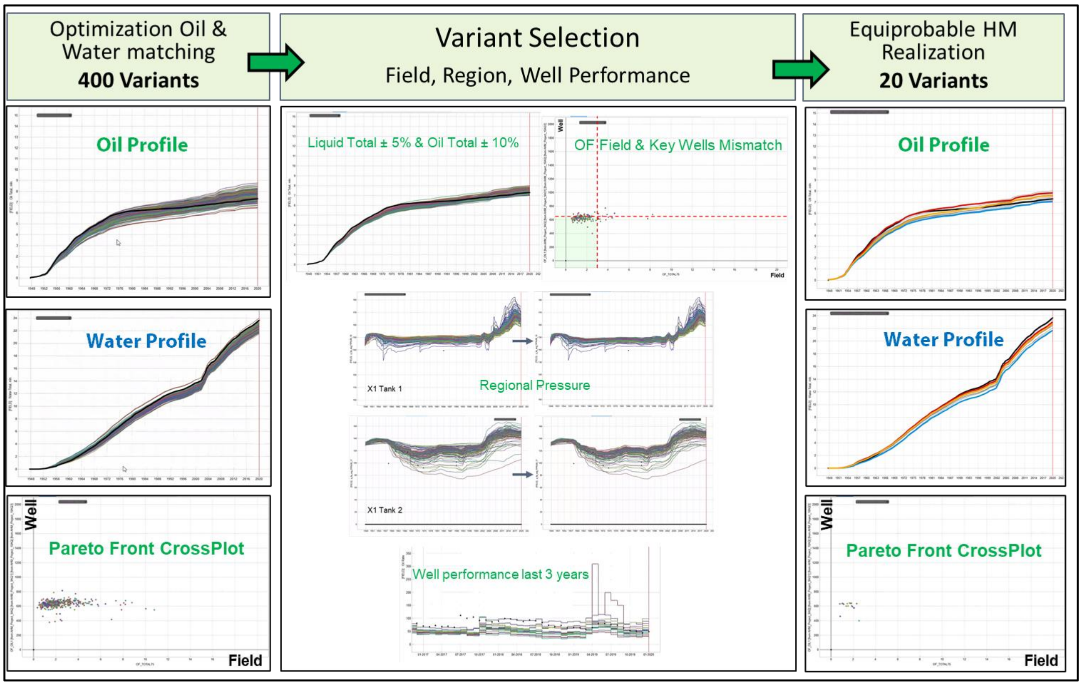


Figure 5. Probabilistic history matching criteria

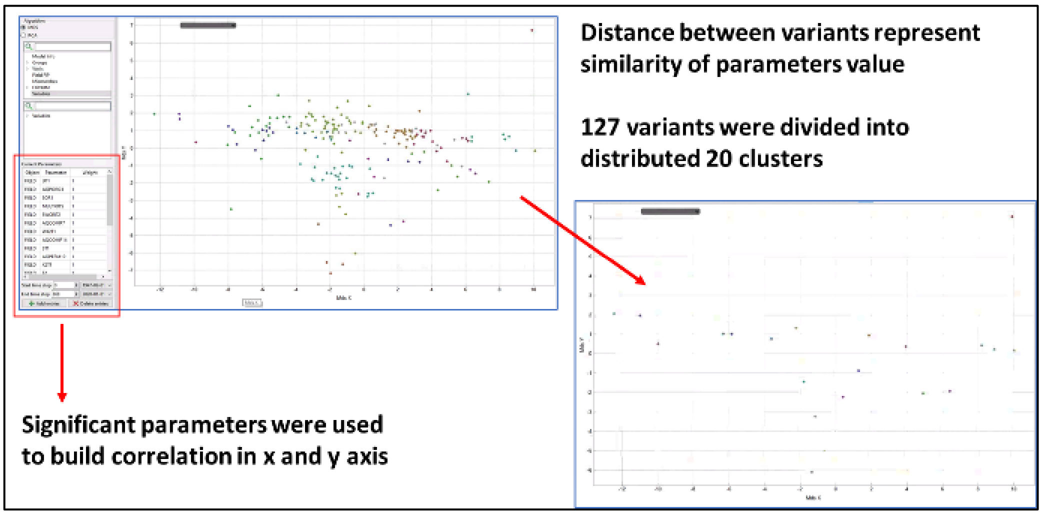


Figure 6. Multi-variant selection

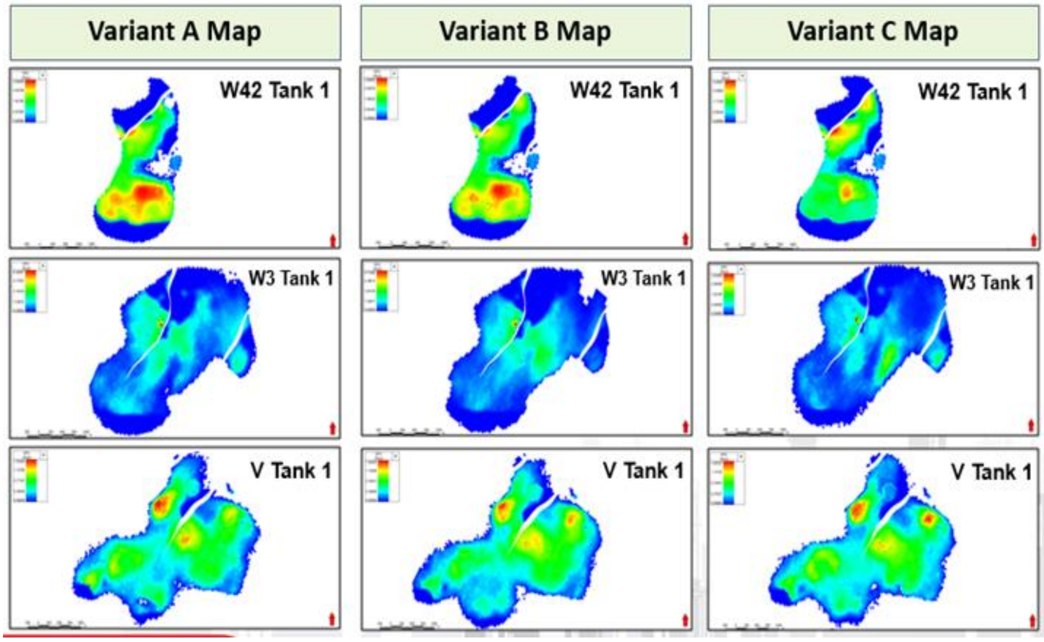


Figure 7. Subsurface risk assessment

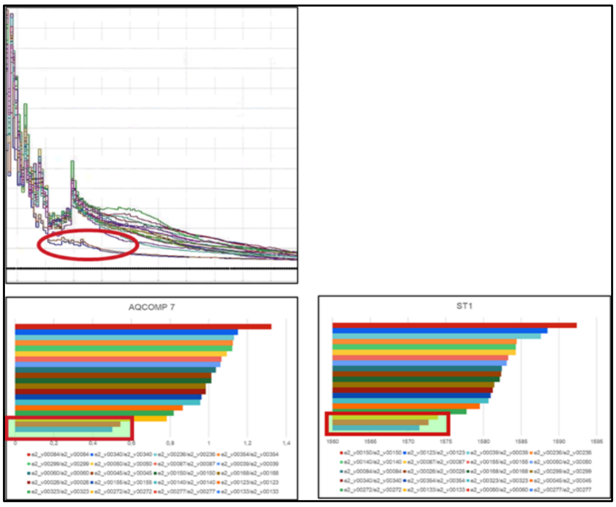


Figure 8. Key uncertainty parameters