

## Improved History Matching and Uncertainty Quantification Using an Ensemble Based Approach, Case Study S-Field Sumatra

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**Abstract.** The purpose of reservoir modeling is to solve the inverse problem by building a 3D mathematical model of the reservoir using measured data. To minimize the investment risk and make the best decision for field development strategy, reservoir engineers have to build a reservoir model close to the actual condition. Understanding the field, including the uncertainties, is essential to make a trusted reservoir model prediction. The traditional approach to reservoir modeling and history matching is looking for one single base case model using a trial error approach to get a history-matched model. Reservoir modelers commonly use the conventional method. Therefore, it has a limitation in quantifying the model uncertainties that can lead to model inconsistencies between static and dynamic data measurements during the history matching process. A step-wise manner in modeling using a traditional approach can limit the interaction between different subsurface disciplines during the model generation and history matching. The generated model might perfectly match the current dynamic data measurements but fail to honor the static data and the geological concept.

We applied an ensemble-based approach combined with machine learning software in S-Field to quantify the uncertainty parameters using a probabilistic approach during the history matching process, which enabled the automatic generation of multiple equiprobable realization models under uncertainties. Firstly, an initial ensemble of models is generated to capture the uncertainties in all parts of the modeling process. A dynamic modeling workflow is created to input dynamic modeling parameters. We introduce uncertainty in permeability endpoints and capillary pressure curves in all facies types. There is no SCAL data in S-Field, so permeability needs to be calculated using correlation, and it proved to be a challenge to find a suitable range. Creating the initial ensemble (CIE) process is done by doing facies modeling and petrophysical modeling, introducing concept probability for facies distribution to honor the existing geological concept. The match level difference between the observed data and generated model can be assigned from the initial ensemble result. Then the uncertainty parameters that should be modified in the history matching process are identified to achieve an initial ensemble that covers and follows the observed data's trend. Finally, the history matching process is done by performing a computational step with several iterative methods to achieve an ensemble of reservoir models that match observed data.

The proposed workflow and method can be the case solution to capture the uncertainties when we want to achieve reservoir models which consistently honor the static data and geological concept. Hence, the result of an ensemble reservoir model can be used to decide the best development strategy and minimize investment risk. Moreover, we can effectively utilize all available data consistently using the integrated workflow.

**Keywords:** reservoir, uncertainty, ensemble, history matching, probabilistic

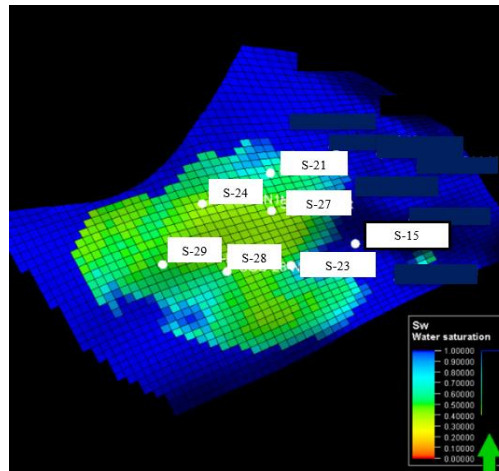
### 1. Introduction

Traditional history matching methods are generally limited to several variables and a small amount of data. The dynamic data conditioning process is one of the biggest challenges in this approach. The traditional reservoir modeling and historical matching approach find a single base case model using trial and error exercises. The reservoir model in this approach will be re-parameterized to change the uncertain parameters simultaneously to match the dynamic data. It enormously depends on the reservoir engineer's experience and ability to understand the reservoir model behavior. Therefore, it may cause model inconsistency between static and dynamic data measurements during the history matching process.

In this paper, we present the effectiveness of a fully integrated approach for ensemble-based history matching in the S-Field, which is an oil field located in Jambi, Indonesia. The S-Field has two main layers of sand, the first layer is N sand that has been produced, and the second layer is N1 sand that is located below N. The N sand layer and N1 sand are included in the Air Benakat Formation, which was deposited in the coastal environment. That two layers of sand are typically blocky and thick reservoirs.

## 2. Data and Methodology

Layer N1 sand has been produced for four years, and it has six wells that need to be analyzed for history matching, as shown in **Figure 1** below.



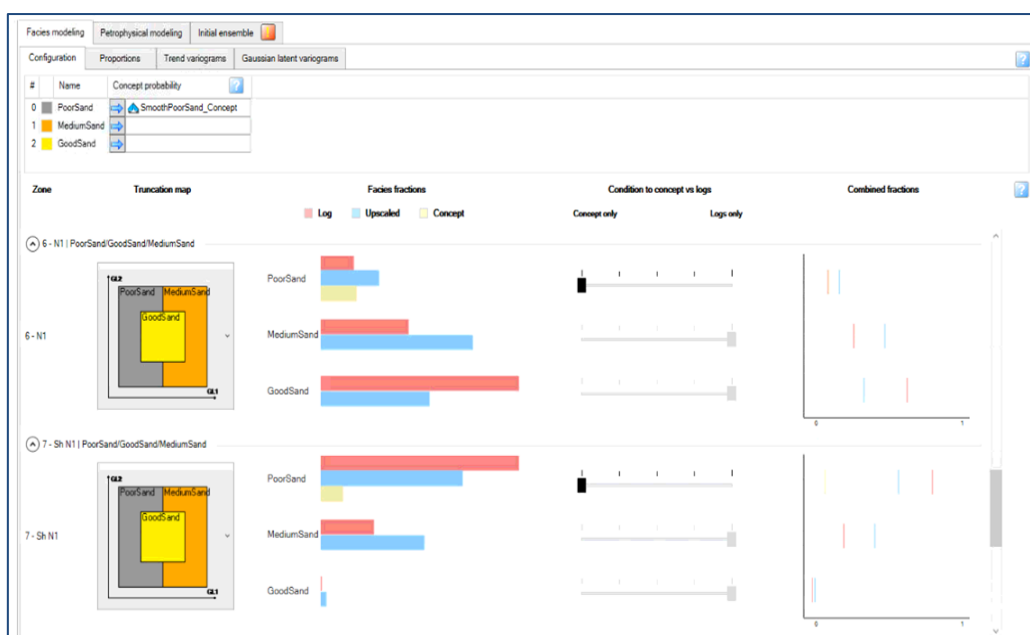
**Figure 1.** Water Saturation ( $S_w$ ) Map

### 2.1. Ensemble-based History Matching

This paper uses an ensemble-based approach with a probabilistic method for history matching. We use an ensemble-based approach to quantify the model uncertainties that lead to model consistencies between static and dynamic data measurements during the history matching process. After checking the data input quality, an initial ensemble needs to be set for creating an ensemble that covers the necessary production and pressure data with uncertainty, using equally likely realizations that honors the prior geological and reservoir engineering concept. The Ensemble-based simulation study (EBSS) process will consume the initial ensemble for history matching.

### 2.2. Facies Definition

The facies are defined into three facies based on the PHIE log. The first facies are PoorSand (non-net, facies 0) with  $PHIE < 0.01$ . The second facies is MediumSand (shaly sand, facies 1) with  $0.01 \leq PHIE < 0.16$ . The Last facies is GoodSand (sand, facies 2) with  $PHIE \geq 0.16$ . We introduce concept probability for the PoorSand portion to honor the existing geological concept, as shown in **Figure 2**.



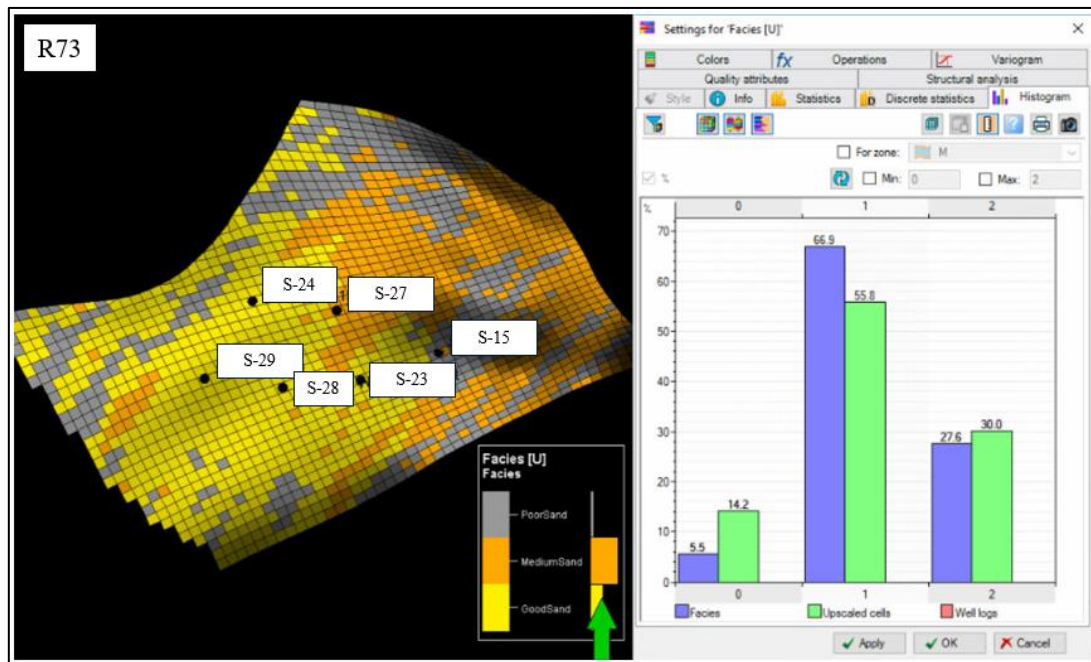
**Figure 2.** Facies Modeling Configuration

### 2.3. Petrophysical Modeling

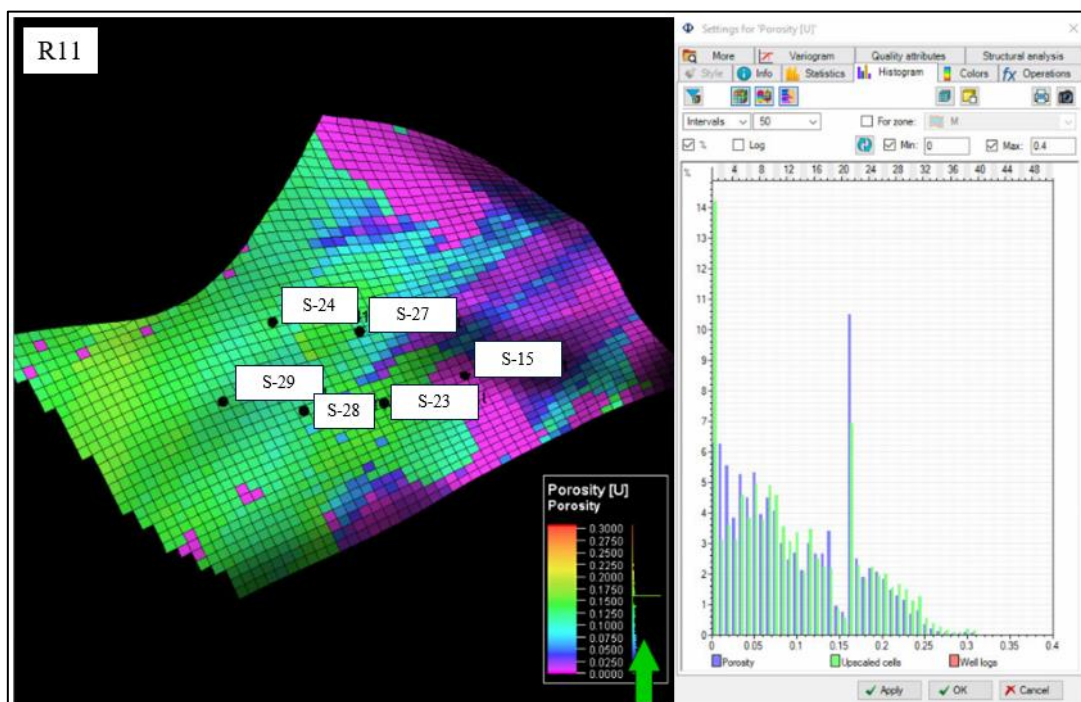
We introduce petrophysical modeling using well log upscaling with a random pick to capture the well log data distribution in the 3D properties.

### 3. Results and Discussion

After generating a realization for the facies modeling, the result honored the upscaled cell distribution. 3D facies proportions follow the upscaled cell distribution for all realizations. Since the random pick-upscaling method is used, we are also honoring well-log data. Seventy-five equiprobable realizations are generated and embrace uncertainties from several geological properties. One of the realization results is shown in **Figure 3**. Similar to facies modeling, 3D properties distributions follow the upscaled cell distribution for all realizations, as shown in **Figure 4**. (Porosity distribution).

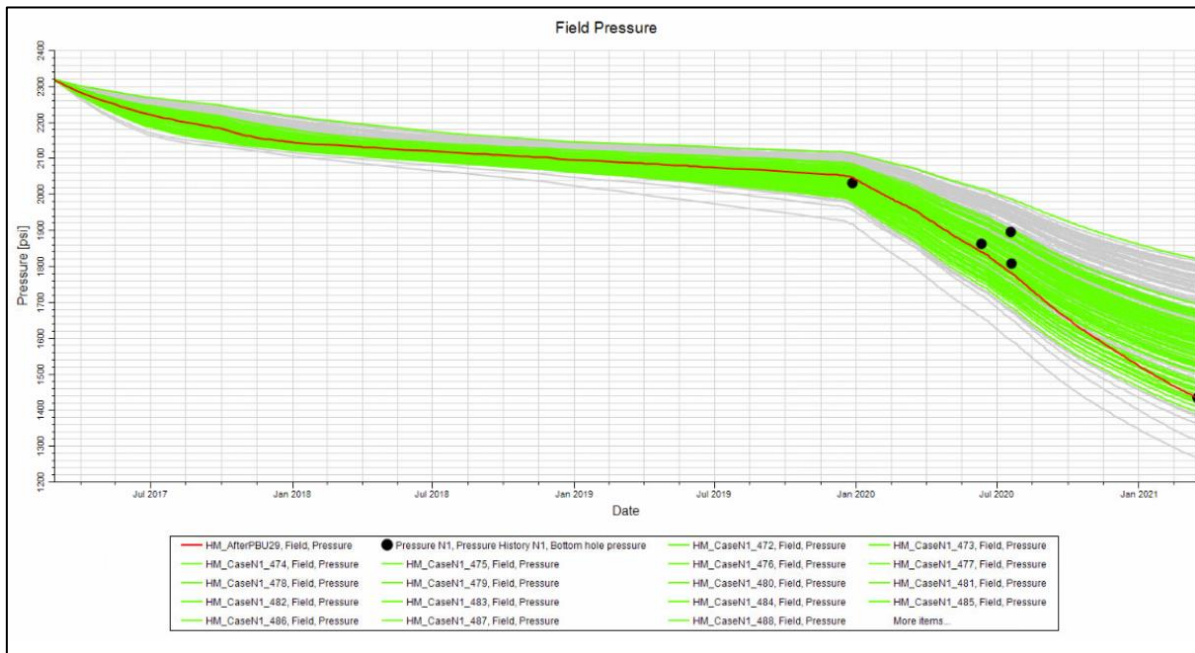


**Figure 3.** Facies Modeling Realization

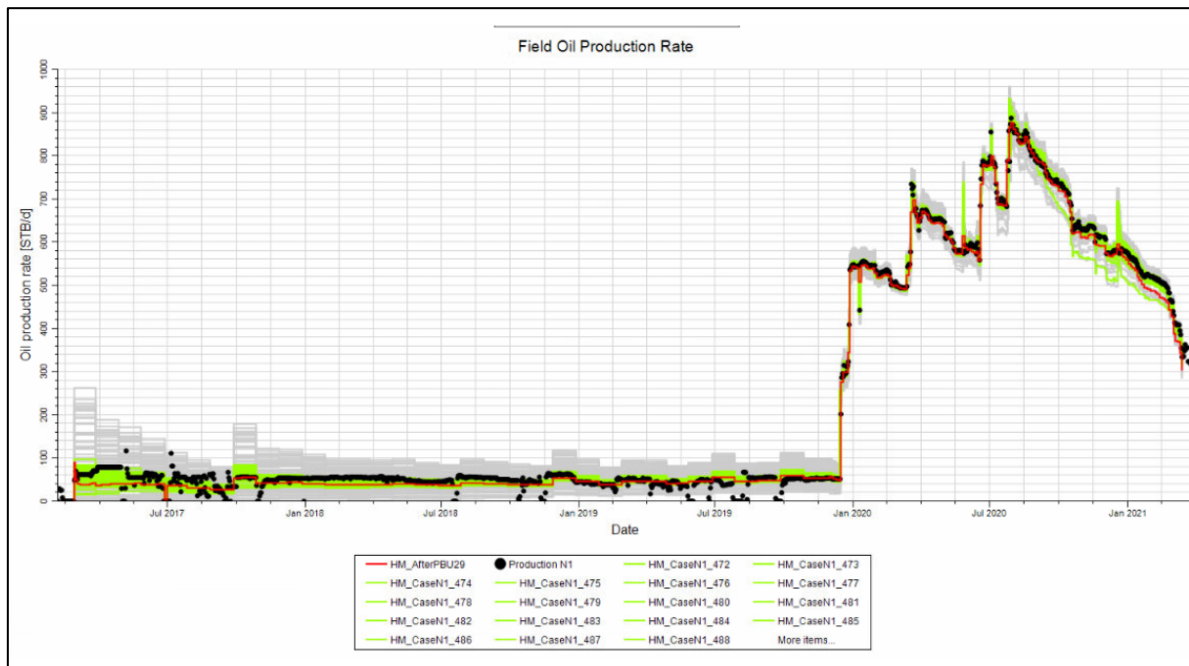


**Figure 4.** 3D Properties Distribution – Porosity Distribution

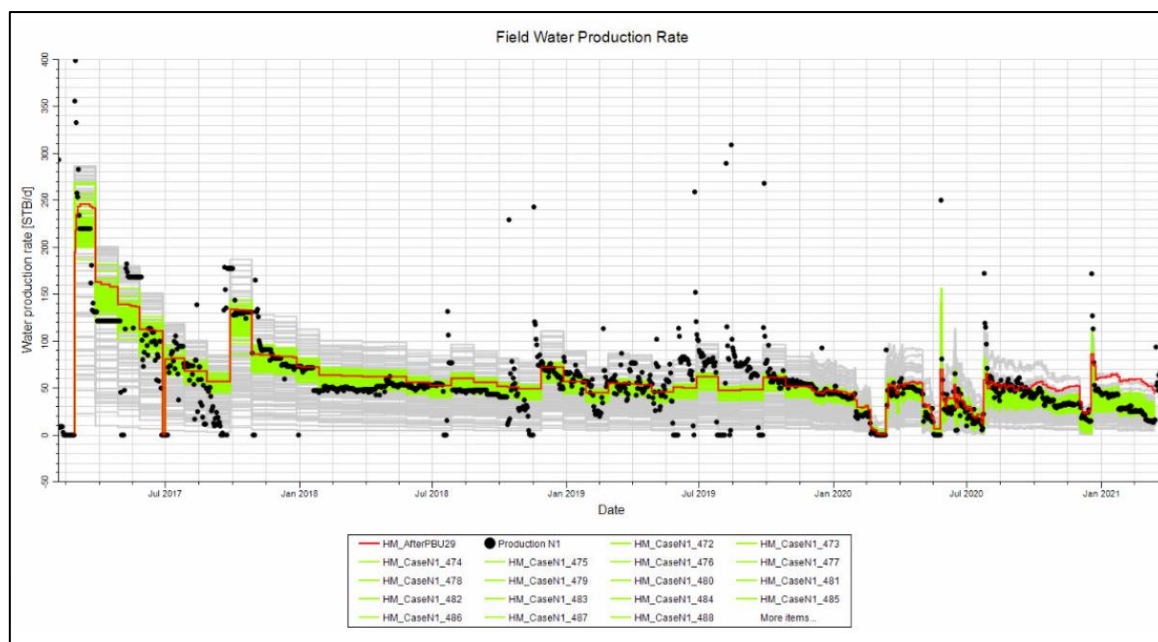
**Figure 5.** shows the initial ensemble results for field pressure (grey lines) compared to posterior ensemble results (green bars), single case (red line), and observed data (black dots). The ensemble-based history matching result captures observed data better than using only a single case. The technology of the machine learning tool is used to update the model and minimize the mismatch between final ensembles. Four iterations of history matching have been run to get a result closer to the observed data. Field oil production match has been improved compared to the initial ensemble, especially for the early production, as shown in **Figure 6**. The posterior ensemble follows the observed data trend. The field water production match has been improved compared to the initial ensemble, as shown in **Figure 7**.



**Figure 5.** History Match Result – Field Pressure



**Figure 6.** History Matching Result – Field Oil Production Rate



**Figure 7.** History Matching Result – Field Water Production Rate

Using ensemble results, essential statistics related to oil in place can be obtained. FOIP results in P10, P50, and P90 of the original and remaining oil in place can be estimated, as shown in **Table 1**.

**Table 1.** FOIP Result P10, P50, and P90

FOIP (STB)	OOIP (STB)	Remaining Oil (STB)
P10	3.405.440	3.073.373
P50	4.262.468	3.927.611
P90	5.187.567	4.851.209

#### 4. Conclusions

Based on our study, we can summarize that the approach and method can be the case solution to capture the uncertainties when we want to achieve reservoir models which consistently honor the static data and geological concept. Hence, the result of an ensemble reservoir model can be used to decide the best development strategy and minimize investment risk. Moreover, we can effectively utilize all available data consistently using the integrated workflow.

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