University of Alberta

Use of Temperature data for assisted history matching and characterization of SAGD heterogeneous reservoirs within EnKF framework

by

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Abstract

The Ensemble Kalman Filter (EnKF), a parameter estimation approach using the real-time DTS temperature observations is proposed for automatic history matching and quantitative reservoir characterization of SAGD reservoirs. EnKF algorithm is coupled with the discrete cosine transform (DCT) for updating reservoir models whose petrophysical properties are not necessarily Gaussian. The DCT-EnKF provided a highly attractive algorithm for parameterizing the facies labels in SAGD reservoirs. Furthermore, to capture geologically meaningful and realistic facies distribution in conjunction with matching observed data, we included fiber-optic sensor temperature data.

Several cases with different facies distribution and well configurations were studied. In order to investigate the effect of temperature observations on SAGD reservoir characterization, the number of DTS observations and their locations were varied for each study. The qualities of the history-matched models were assessed by comparing the permeability maps, facies maps and the Root Mean Square Error (RMSE) of the predicted data mismatch. Finally, sensitivity analysis was performed to obtain an optimum number of sensors and their locations for improved reservoir characterization. Use of temperature data in conjunction with production data demonstrated significant improvement in facies detection and reduced uncertainty for SAGD reservoirs. The results reveal that increasing the number of temperature observations showed very little improvements after some critical number of sensor observations. At the end, the methodology has been applied to a real SAGD reservoir.

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Chapter 1

Introduction

The Steam Assisted Gravity Drainage (SAGD) provides significantly greater production rates, high recoveries, and lower Stem-Oil ratio (SOR), as compared to conventional surface mining extraction techniques and other thermal recovery methods. It is due to these advantages that the SAGD technique is considered the most promising process for recovering Athabasca oil sands' deposits, which contains 140 billion cubic meters or one trillion barrels of bitumen-in-place; this amount accounts for 20% of Canada's total oil reserve and two-third of Alberta's.

The quantitative reservoir characterization of heterogeneity and determination of shale barriers are important for uncertainty assessment and prediction of production performance. This also aids in identifying the reservoir zones with the greatest SAGD potential and selecting the optimal number of SAGD wells for production. The shale barriers act as flow barriers depending on their size, location, and continuity throughout the reservoir. The long continuous shale barriers are important to characterize, as they are the barriers for steam migration which greatly influences the reservoir performance; however, the short horizontal shale barrier does not have much effect on the reservoir performance (Butler et al, 1992). Reservoir characterization studies involve integration of several measurements such as seismic data, well log data and core data into the geological model to enable construction of multiple conditional or unconditional realizations of the various property fields. However as these measurements are expensive to acquire, the geological models are associated with several uncertain parameters due to which there is a lot of uncertainty in the reservoir performance estimates. The dynamic production data (oil production rate, water cut, bottom hole pressure, temperature etc) on the other hand provide an additional level of information with which the geological models are calibrated to reduce the uncertainty associated with the reservoir description. These data are more valuable than periodic measurements, as they provide accurate information about what is going on in the well and the reservoir.

Both the heavy computational burden and high data sampling frequency requires a computationally efficient data assimilation algorithm that have the capability to simultaneously use all the recorded data to provide uncertainty assessment by generating multiple plausible reservoir models. Flexibility to assimilate diverse data types and simple simulator coding algorithm are another requirements. The Ensemble Kalman filter (EnKF) has emerged as a promising approach for real-time updating of reservoir models. The Ensemble Kalman Filter (EnKF) is a recursive filter that was first introduced by Evensen in 1994 as an extension to the traditional Kalman filter to nonlinear problems. It uses an ensemble of models from which all necessary statistics (e.g., model parameter and response relation) can be calculated. The EnKF has been successfully used in weather forecasting, oceanography, and hydrology (Evensen et al, 2002; Margulis et al, 2002). However, in these applications, only dynamic variables were tuned. The

EnKF algorithm had been successfully applied in the petroleum industry for reservoir characterization as well as matching real-time multiphase production data [Naevdel et al, (2005), Oliver et al, (2004), Chen et al, (2005), Evensen et al, (2007), Gul et al, (2011)].

1.1 Problem Definition

The process of calibrating the uncertain reservoir model parameters to minimize the difference between the model predictions and field observations is called history matching. Traditional history matching involves manually tuning the reservoir parameters followed by matching dynamic data on a well-by-well basis and consequently, can be very time consuming for large reservoirs with a large number of wells. In traditional history matching, uncertainty assessment usually through repeated history matching with different initial models, which makes the process more CPU demanded. Also traditional history matching does not allow continuous model updating. When new production data are available and are required to be incorporated into the reservoir model, the traditional history matching process has to be repeated using all the measured data. This limits the applicability of the traditional history matching techniques to small and simple reservoir models. Automatic history matching, on the other hand, allows calibrating the reservoir model through the use of algorithms that are designed to honor prior observations and preserve geological characteristics of the reservoir. This method has the capability to match large set of data and model parameters and greatly reduce the history matching time. The automatic history matching can be broadly classified into two types: (a) Gradient based method which solves the inverse problem using the gradients or parameter sensitivities of an appropriately constructed objective function. However this approach becomes computationally demanding when generating multiple history matched model realizations which involves repeated application of the procedure to each realization (b) stochastic approaches which again are slow to converge, requires repeated turnarounds for model calibrations. Recently the data output frequency has increased due to the increased deployment of permanent sensors for monitoring pressure, temperature or flow rates. Thus it becomes very important to maintain 'live reservoir model' incorporating the data as soon as they become available so that the reservoir model is always up-to-date. A new kind of history matching algorithm is thus required that can use all the recorded information for fast and continuous model updating by generating multiple plausible reservoir models. A recent and promising inverse modeling approach that combines these capabilities called the Ensemble Kalman Filter (EnKF) is proposed to continuously and simultaneously characterize and history match the petroleum reservoir model based on the observations of dynamic parameters and uncertainty quantification using the static parameters.

1.2 Objective

The principal objective of this thesis is to develop a methodology using the Ensemble Kalman Filter (EnKF) parameter estimation approach along with the real-time temperature observations to provide a highly attractive algorithm for reservoir characterization, automatic history matching and shale barrier detection in SAGD reservoirs. In this work, the Ensemble Kalman filter has been refined for applications to the problem of non-Gaussian distributions by combining the EnKF with discrete cosine transform parameterization (DCT) approach. Considering two case studies, a single facies and a two facies SAGD model, we have shown several cases to compare the benefits of including temperature observations along with the production data during the data assimilation step in EnKF. Sensitivities of using different number of temperature observations and their locations within the SAGD reservoir for uncertainty assessment are also investigated in this thesis.

1.3 Thesis Overview

This thesis consists of eight chapters. Chapter 1 gives a brief overview of the Steam assisted gravity drainage (SAGD) process and also states the challenges associated with it. This chapter also explains the aim of the research and the methodology adopted to address the problem statement. Chapter 2 is devoted to the introduction of Kalman filter (KF) algorithm and the Ensemble Kalman filter (EnKF). A detailed literature review on the application of this method in petroleum reservoir model characterization, along with EnKF's most recent modifications is also included in this chapter. Chapter 3 proposes the EnKF methodology for continuous reservoir model updating using production data along with the temperature observations for characterizing and history matching SAGD reservoirs. The equations involved in the Ensemble Kalman filter (EnKF) based petroleum model updating is also explained in detail in this chapter. Chapter 4 comprises of implementation details of EnKF carried out on a synthetic single facies SAGD reservoir model. The aim of this study was to detect high and low permeability regions in a SAGD reservoir by using temperature observations along with the production data during the data assimilation step and tuning permeability distributions. A sensitivity analysis of using different temperature observations is also carried out to obtain an optimum number of temperature observations to be used for SAGD model updating. Chapter 5 and 6 shows the application of the EnKF methodology for 2D and 3D SAGD models having shale and sand facies. This study aimed at detecting long continuous shale barriers in SAGD reservoirs by the use of continuous temperature observations along with the production data. Similar to the previous chapter, a sensitivity analysis is carried out to come up with the optimum number and location of temperature observations for SAGD reservoir characterization and history matching. Chapter 6 shows the implementation of the proposed methodology for a realistic 3D SAGD case study. ConocoPhillips's Surmont SAGD reservoir simulation model is used for this study. Finally, Chapter 8 presents the summary and conclusion of the conducted study, discusses possible modifications to the proposed algorithm.

Chapter 2

The Ensemble Kalman Filter –Introduction and Background

The data assimilation processes has seen great progress during the last couple of decades especially in the atmospheric and oceanographic sciences. The data assimilation involves continuous integration of available information into a numerical model, typically a geophysical system. For example, the atmospheric models should include the most recent observations such as temperature and atmospheric pressure for better weather forecast. A major challenge in data assimilation is the inclusion of massive available data into these models real-time. These challenges introduced improvements in traditional data assimilation processes to be capable of handling large amounts of data and more severe nonlinearities. One of the widely used data assimilation technique is the Kalman filter method, introduced as a recursive solution to the discrete data linear filtering problem. The Kalman filter is an optimal recursive data assimilation algorithm which estimates unknown variables using series of measurements observed over time, containing noise and other random inaccuracies.

2.1 Outline of Kalman Filter Algorithm

The Kalman filter was first developed in the 60's by Kalman and Bucy (Kalman, 1960; Kalman and Bucy, 1961) as a data assimilation technique for estimation of linear dynamic systems. With Kalman filter, a model equation containing the current state of the system (associated with an uncertainty expressed by covariance matrix) and an observation equation that relates a linear combination of the states to measurements is always available. The measurements are also available with uncertainty. These model equations are used to calculate the state variables forward in time with the current estimate of the state as initial condition. Wide applications of the Kalman filter algorithm can be found in the fields of satellite navigation systems, seismology, 3D modeling, dynamic positioning and weather forecasting, to name a few.

The Kalman filter provides a recursive solution to the discrete data linear filtering problem in two steps: a forecast step and an update step.

Forecast step or the prediction step produces the estimates of the current state variables thus evolving the state vector forward in time between two consecutive measurement times. The dynamic system model equation is given by following Formula:

$$y_k = \Psi_{k-1} y_{k-1} + w_{k-1} \qquad (2.1.1)$$

The evolution of state vector is

$$y_k^p = \Psi_{k-1} y_{k-1}^u \qquad (2.1.2)$$

Where the subscripts k and k-1 are time indices for measurement time t_k and t_{k-1}, where measured data are available. y_k^p represent the prior state vector at time t_k. The prior state vector is the direct output of the dynamic system before updating. y_{k-1}^u represent the updated state vector obtained after the data assimilation step. Ψ_{k-1} is the state transition matrix that transits the state vector from time t_{k-1} to time t_k. wk-1 is the model error with covariance Q_{k-1}.

$$C_{Y,k}^p = \Psi_{k-1} C_{Y,k-1}^u \Psi_{k-1}^T + Q_{k-1} \qquad (2.1.3)$$

$C_{Y,k}^p$ is the covariance matrix associated with the prior state vector. It is calculated by propagating an assumed initial covariance matrix of the state vector at time 0, $C_{Y,0}^u$ through time. $C_{Y,k-1}^u$ is the updated covariance matrix after data assimilation step at time t_{k-1}.

At the update step, the prior state vectors are updated using the new observed data:

$$y_k^u = y_k^p + K_k(d_{obs,k} - H_k y_k^p) \qquad (2.1.4)$$

Where K_k is the Kalman gain matrix which is computed as follows:

$$K_k = C_{Y,k}^p H_k^T (H_k C_{Y,k}^p H_k^T + C_{D,k})^{-1} \qquad (2.1.5)$$

Here $C_{D,k}$ is the data error covariance matrix. The analyzed covariance matrices are updated as follows:

$$C_{Y,k}^u = (I - K_k H_k) C_{Y,k}^p \qquad (2.1.6)$$

The above two step procedure is at repeated at each measurement time and is continued till the last data is assimilated. The Kalman filter is based on the assumption that model and measurement errors are Gaussian, unbiased and are not correlated in time. Hk is a matrix operator that relates the state vector to the production data.

Applications of the Kalman filter can be found in estimating petroleum model variables (Eisenmann et al, 1994; Corser et al, 2000). However Kalman filter can only be applied when there are relatively small numbers of variables and when the variables to be estimated are linearly related to the observations. Most data assimilation problems in petroleum reservoir engineering are highly non-linear and characterized by many variables. The Kalman filter was extended to work with nonlinear dynamic models through the extended Kalman filter (EKF), replacing the equation 2.1.2 by following formula:

$$y_{k+1}^{p} = F_k(y_k^u) \qquad (2.1.7)$$

Here F_k is the state transition matrix. The extended Kalman filter uses linearization of the dynamic model and observation equations. However for highly non-linear systems the extended Kalman filter fails and the equations that need to be solved using EKF becomes infeasible because of the problem calculating and updating the covariance matrix C_y. Evensen (1994) introduced Ensemble Kalman Filter (EnKF) as a solution to resolve some of the problems the EKF. The suitability of EnKF for highly-linear dynamic problems is shown by many researchers (Zang and Malanotte-Rizzoli, 2003; Bertino et al, 2003). Since its introduction in 1994, the EnKF has been widely used in the meteorology, oceanography and ground water hydrology (Evensen and van Leeuwen, 1996; Evensen, 1997, 2003; Houtekamer and Mitchell, 1998, 2001; Anderson and Anderson, 1999; Hamill et al, 2000; Reichle et al, 2002; Chen and Zhang, 2006).

2.2 Applications of the Ensemble Kalman filter in petroleum reservoir engineering

The Ensemble Kalman filter (EnKF) is a Monte Carlo approach in which an ensemble of models is used from which the covariance matrix of the state vector is directly estimated. Thus in EnKF, the higher order statistical moments are kept when the non-linear dynamics is propagated forward in time.

The use of EnKF technique for continuous updating of a reservoir model is applied for the first time by Geir Nævdal et al, (2002a and 2002b). In these papers, EnKF is applied for near-well reservoir monitoring, focusing on its performance in forecasting the future production. Both model parameters and state variables are used to update the reservoir model. The EnKF methodology is initially applied to a simple synthetic reservoir model which is updated with the forecasts consistent with the measurements. Later this methodology is applied to a semi-synthetic 2D-field model from the North Sea with larger number of state variables. The static parameter updated using EnKF was permeability distribution and the measurements used in the data assimilation step were bottom-hole pressures, water cuts and gas-oil ratios. The efficiency and robustness of EnKF is clearly demonstrated as the results showed significant consistency between measured and predicted values.

Yaqing Gu and Dean S. Oliver examined the application of EnKF on a PUNQ-S3 small-scale synthetic reservoir model constructed on the basis of a real field operated by Elf Exploration Production. The PUNQ (Production forecasting with Uncertainty Quantification) project is used to compare methods for quantifying uncertainty assessment as a joint venture by European research institutes, companies and universities. Dean et al. applied EnKF to this model and compared the results with other traditional data integration methods. EnKF proved out to be an efficient approach for predicting the oil production rate as compared to other data integration methods. The after history match oil production rate prediction obtained from the ensemble of corrected models was in agreement with the truth. However there was overshooting problem in the porosity and permeability fields and they were not matched well. Later Gu implemented the EnKF with a one-dimensional, two-phase waterflood problem and a two-dimensional, two phase problem (Gu and Oliver, 2006). These cases were selected to investigate two primary concerns in application of the EnKF. The first concern was the response of the EnKF in cases when the covariance matrix provides poor representation of the distribution of variables. The second concern was the representation of covariance matrix using lower number of ensemble members. Gu concluded that the forecasts were consistent with the real data and that the constructed model honors all the measured data. However the results also indicated the need of relatively larger ensemble members to obtain stable results, particularly for the reliable assessment of uncertainty. This leads to high computational work and costs.

Later Wen and Chen added a confirming option to the EnKF algorithm to ensure that the updated static and dynamic variables are always consistent and also

avoids nonphysical values for the updated dynamic data (Wen and Chen, 2005). They used a 2-D synthetic reservoir model to illustrate the application of the newly developed EnKF methodology in which permeability is chosen as the tuning parameter to match the real-time multiphase production data. Sensitivity analysis is also carried out using different ensemble size and different covariance models. They found that a relatively large ensemble size is required to accurately estimate the uncertainty of the model parameters. However small ensemble size is capable of providing better production data match. They also found out that if the available production data are of the same type and from the same wells for long time, there is less updating of the reservoir model in the data assimilation step. Yan and Zhang (2005) also conducted a sensitivity analysis of the EnKF methodology based on different ensemble size and also based on varied ensemble type and observation data assimilation timing. They showed that early production data contains more useful information about the reservoir heterogeneity and plays an important role in forecasting state variables. They also showed that if the prior statistics are far apart from the benchmark case, the predicted values might never converge to the measurements and observations.
Lorentzen et al. (2006) applied the EnKF methodology for controlling downhole chokes so that the water flooding is optimized. They used EnKF to optimize either the total cumulative oil production rate or NPV. The results showed that EnKF provided better results as compared to the Partial Enumeration method.

Jafarpour et al, (2007) combined the EnKF algorithm with a flexible and effective parameterization method, the Discrete cosine transform to address the challenges in history matching of large reservoirs such as scarcity of available measurements relative to the number of unknowns leading to ill-posed inverse problem and computational effort required for large reservoir problems. Implementing the above approach using two waterflooding examples showed that with DCT parameterization the results are almost identical to the results obtained with a much more expensive approach that estimates states in every block of the simulator computational grid. Thus the proposed approach proved to be efficient in providing efficient estimation of unknown geological properties in large reservoirs.

Huseby et al, (2009) discussed the integration of natural and conventional tracer data in reservoir modeling using the EnKF. These data sources are mostly unused source of information and are underexploited as a source of data for reservoir modeling. The use tracer data along with production data in EnKF estimation is contrasted to estimations without tracer data. The results have shown that improved estimates of porosity and permeability fields are obtained using natural tracers in data assimilation step.

Chitralekha et al, (2010) demonstrated the efficacy of the EnKF algorithm taking into account the geological heterogeneity of SAGD reservoirs for history matching of SAGD reservoirs. This was the first use of EnKF algorithm for history matching and characterizing SAGD reservoirs. Gul et al, (2011) implemented a constrained-based Ensemble Kalman Filter for characterization, production management and history matching of SAGD reservoirs. The first constraint was applied to the updated permeability values where permeability of each layer was confined to predetermined values. The second constraint was applied to temperature observations and specific temperature data were taken into account at different update steps. The results indicated that using real-time temperature observations during data assimilations step led to better prediction of geological heterogeneity and reservoir's response to well adjustments.

Nejadi et al, (2011) proposed a entropy weighted EnKF (EWEnKF) technique for updating non-Gaussian reservoirs. The Entropy is an excellent normalized measure of the spread of any given probability distribution is entropy, which is a general uncertainty measure on random variables. A weighting factor based on linear combination of mismatch in entropy of model parameters and forecast mismatch was introduced to compute the ensemble mean. It allowed the simultaneous reproduction of non-linear system dynamics and honoring of reference model distributions. The implementation of this methodology was carried out in two synthetic models and the results revealed that EWEnKF has a significant potential to resolve the shortcomings of traditional EnKF in reservoir characterization and history matching of reservoirs exhibiting complex heterogeneities. A continuation to this work, Nejadi et al, (2012) proposed a re-sampling procedure to correct for the loss of non-Gaussian contributions in model parameters are EnKF update and to honor the reference distribution obtained from static geological information. The proposed algorithm involves combining the P-Field re-sampling with the DCT-EnKF approach which is successfully implemented for facies detection of multiple (three) facies model.

They also carried out smoothing algorithm to correct for the short-scale variability of the distributions. A detailed review on the most recent findings on the EnKF application is covered by Aanonsen et al, (2009) and Oliver et al, (2010)

Chapter 3

Ensemble Kalman Filter Methodology & Workflow

The EnKF methodology consists of three steps: (a) forecast step based on the current state variables (b) the data assimilation step in which Kalman gain is computed using the most current production data (c) the update step in which the state variables are updated using the previously computed Kalman gain.

The state variable consists of three types of parameters:

$$y_{k,j} = \begin{pmatrix} m_s \\ m_d \\ d \end{pmatrix}_{k,j} \tag{3.1}$$

Here $y_{k,j}$ is the j[th] ensemble member of the state vector at time t_k. m_s are the static parameters (e.g., porosity and permeability distributions) that do not vary with time. m_d represents the dynamic parameters such as pressure and phase saturation values that are the solution to the flow equations and thus are parameters changing with time. The production data such as oil production rate, water injection rate, bottom-hole pressure, temperature etc. are represented by d. k denotes the time steps at which data is assimilated.

The typical workflow of a EnKF is described as follows:

1. The first step involves generating initial ensembles of state vectors. At the starting time (time=0) we assume that no production data is available.

$$\Psi = \{y^1, y^2, y^3, \dots \dots .., y^{Ne}\} \qquad (3.2)$$

Here Ψ represents the ensemble of state vector and Ne is the total number of realizations in the ensemble. Multiple realizations of state vectors are generated using geostastical methods conditional to the reference permeability distribution to represent the initial uncertainty in the reservoir model. The initial pressure and saturations are assumed to be known without uncertainty.

2. The forecast step consists of running the reservoir simulator for each of the model realizations till the next data assimilation step when new measurements of production data becomes available.

$$y_k^{p,j} = F\left(y_{k-1}^{a,j}\right) + w_{k-1}, j = 1 \dots \dots . Ne \qquad (3.3)$$

Here $y_k^{p,j}$ represents the forecasted state vector at time-step k. *F(.)* is the forecast operator representing the reservoir simulator and w_{k-1} represents the model error. Superscript p and a represents the predicted and updated state vectors. In the forecast step new ensemble of dynamic and production data consistent with the initial static parameters are generated. For large-scale field applications, the forecast step is the most computationally demanding step.

3. The forecast step is followed by the update step whereby the state vectors are updated using the Kalman update equation as follows:

$$y_k^a = y_k^p + K_k(d_k - Hy_k^p) \qquad (3.4)$$

Here the matrix K_k is the ensemble approximation of the Kalman gain for time t_k and d_k represents an ensemble of the sampled observations. H is the matrix operator that relates the state vector to the production data. It simply selects the simulated data from the state vector. The measurement matrix H is given by:

$$H = [\ 0 \ \ \mathrm{I}\ ] \qquad (3.5)$$

Where I is the identity matrix. The Kalman gain (K) is computed as follows:

$$K_k = C_{y_k^p} H^T (HC_{y_k^p}H^T + C_{d_k})^{-1} \qquad (3.6)$$

$C_{y_k^p}$ is the covariance matrix for the state variables at the time t_k that can be calculated from the ensemble of forecasted state vectors using the standard statistical method:

$$C_{y_k^p} = \frac{1}{Ne-1}\left\{\left(y_k^p - \overline{y}_k^p\right)\left(y_k^p - \overline{y}_k^p\right)^T\right\} \qquad (3.7)$$

Here Ne is the number of realizations in the ensemble. $\overline{y}_k^p$ is the mean of the state variables. With K_k and the production data at the assimilating time step (d_k), the updated state vector is calculated using equation (4). To create an ensemble of production data, we add random perturbations to the observed production data. The updated covariance matrix can be computed with the following formula:

$$C_{y_k^u} = (I - K_k H_k) C_{y_k^p} \tag{3.8}$$

Each realization of the updated ensemble reflects the most current production data after the update step.

EnKF work flow for history matching

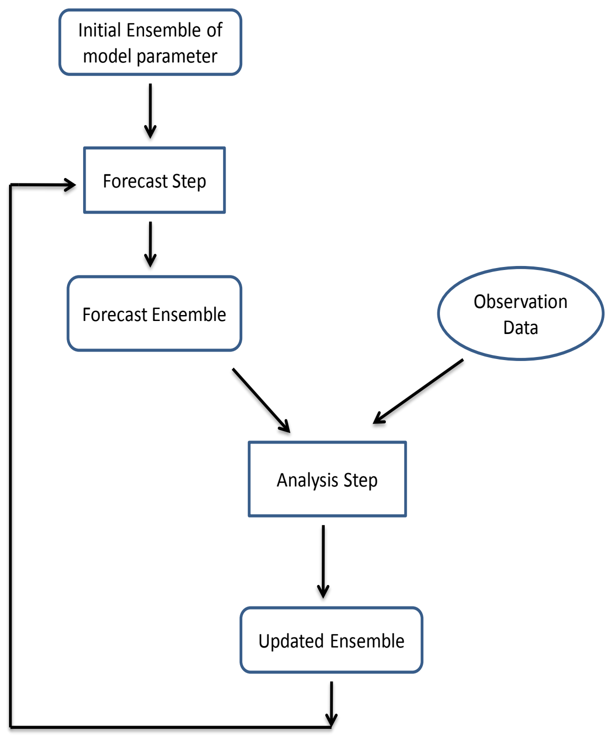


Figure 1: EnKF methodology flowchart for Data Integration (Adapted from Seiler et al, 2009)

As can be seen from the Figure 1, to initiate the EnKF algorithm, initial ensemble of permeability model parameter along with the state variables such as fluid saturations, operating pressure, temperature of the injected steam, PVT and relative permeability curves are prepared. There is no production data available at the starting time (t_0). The initial ensemble is generated using a semivariogram model derived from the permeability data of the benchmark case or the true case. Once the initial permeability ensemble is generated, it can be incorporated into the thermal simulator through EnKF forecast step. For simplicity, it is assumed that reservoir porosity is constant.

Eclipse's E-300 thermal simulator is chosen as the thermal flow simulator. The production data are incorporated into reservoir model sequentially in time as they become available and the ensemble of reservoir models evolves with time, representing the assimilation of measurements at the given time. The reservoir simulation is simply run for one forward time step using the most current state vector to the time at which new production data are available and perform above analysis to update the state vector in order to reflect the new data. With every data assimilation step, there is some degree of increment of quality to the estimation of the reservoir model. The improvement in the quality of the estimation depends on the information the new measurement data is carrying. Also, during history matching, we have an ensemble of updated reservoir models matching the most current production data available at all time that also assists in uncertainty assessment. For traditional history matching, when new measurements needed to be matched the entire history matching process has to be repeated using all the data. This makes EnKF based history matching a probable history matching approach especially when the frequency of data is fairly high as, for example, data from permanent sensors. Thus, EnKF can be built upon any reservoir simulator, which makes the implimentation of EnKF relatively simpler as compared to the traditional gradient based history matching approaches.

Chapter 4

Single-facies 2-Dimensional SAGD reservoir model updating using EnKF

In this chapter and the upcoming chapter we will implement the EnKF methodology to history match and characterize a 2-D single facies and two facies SAGD reservoir model. We used the EnKF equations by preparing the workflow in the MATLAB programming software by interfacing it with the Eclipse E300 for compositional simulation modeling and Petrel RE for petrophysical. The EnKF can be built upon any reservoir simulator, as the simulator acts as a black box in EnKF workflow. This case study consists of a single facies model in which the permeability distribution is the unknown model parameter. Figure.4.1(b) shows the true permeability distribution for the first case study, which was generated using Sequential Gaussian Simulation (SGSim) in Petrel. The reference field has high and low permeability regions, which we aim to detect by the EnKF algorithm based on the real time production and temperature data.

2-D SAGD reservoir models, having 21x1x21 grid blocks with model dimensions of 250 meters x 750 meters x 35 meters, have been used in this case study. A pair of injector and producer is used in the simulation model. The observation data include the oil production rate (Q), cumulative steam-oil ratio (cSOR), and temperature data from different sensor locations. The porosity is assumed to be a constant 35% value throughout the reservoir. The other reservoir parameters are presented in Table (4.1)

Table 4.1: Single Facies Reservoir Model Properties

Table 1: SAGD Model Reservoir Properties	
Model Dimensions	21 x 1 x 21
Length in X, Y, Z direction	250 m x 750m x 35m
Porosity	35%
Permeability Range	Single facies : 1000 to 4000 md
Formation Heat Capacity	7.4E2 KJ/m3/K
Rock thermal Conductivities	2.1E2 KJ/m/day/C
Temperature	18 C
No. Of wells	1 producer & 1 injector
Pressure	30 Bar
Injected Fluid	Steam
Steam Quality	90%
Injection Temperature	285 deg C

4.1 Initial Ensemble Generation

The reference permeability distribution Figure 4.1(b) is generated through the sequential Gaussian simulation (SGSIM) technique using Petrel RE by assuming an exponential geostatistical variogram model with a range of 200 m and 75 m in the major and minor direction, respectively, along with an azimuth angle of 45^o. At the starting time, (t=0) when no production data is available we can see that the initial averaged model Figure. 4.1(a) is featureless and has constant values which are very close to the mean and variance of the input histogram. The *ln* (permeability) was the simulated property whose distribution is assumed to be

Gaussian with a range of 1000 md to 4000 md. The reference permeability distribution, as well as the simulated dynamic data using this reference permeability such as oil production rate (Q), cumulative steam oil ratio (cSOR) and temperature data are considered as true case. The observed data is assumed to be available at the end of every month for 14 years, and they are directly read from the true data.

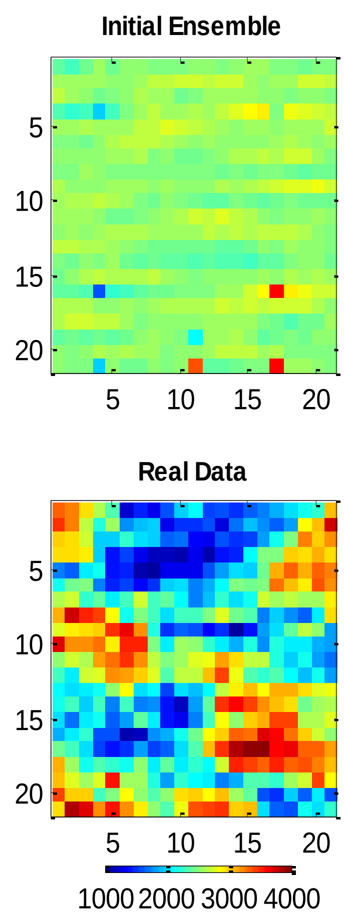
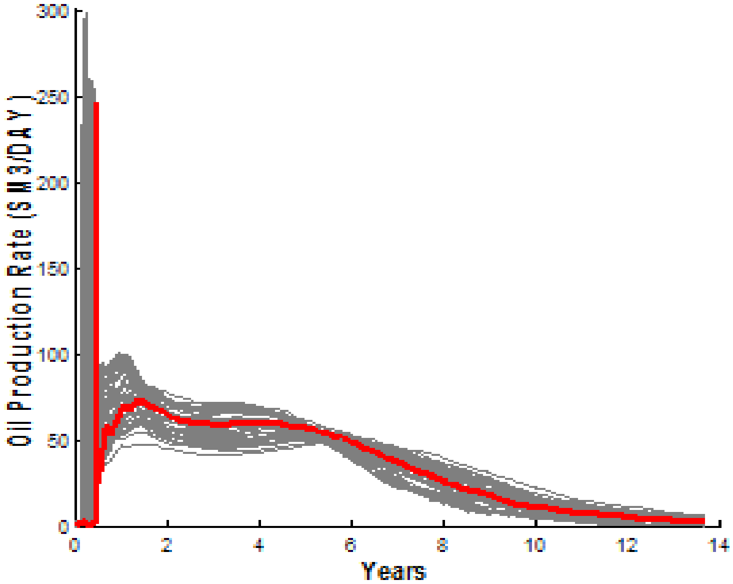


Figure 4.1: Single facies permeability map.
(a): Average of Initial ensemble of permeability models
(b): The Reference permeability field

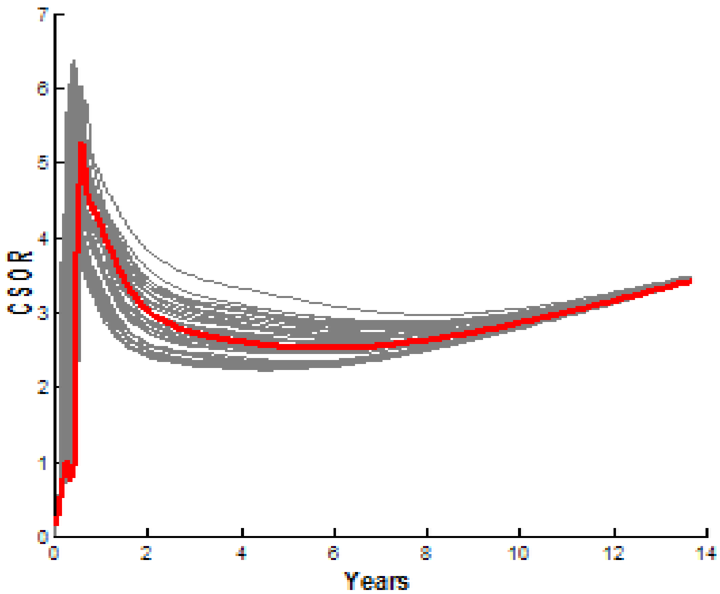
An initial ensemble of 60 permeability models is generated using the SGSIM method with the same histogram and variogram as the reference field. Initial ensemble generation is an important step in EnKF workflow as estimation of the model parameters and prediction of state variables is directly influenced by the covariance structure stored in the initial ensemble models. The initial ensemble of model parameters are generated such that they follow Gaussian distribution, and limiting them to the permeability range according to the reference distribution. These initial ensembles of permeability models are used to generate initial ensembles of state variables (Figure. 4.2). These ensembles of permeability models are input for the EnKF and are updated every 3 months, assimilating the most current observed data. The hard permeability data is assumed to be available at the (4, 1, 4), (4, 1, 16), (4, 1, 21), and (17, 1, 4) grid blocks and well locations and are used as a conditioning data.

Before History match

(a)Production Rate



(b) cSOR



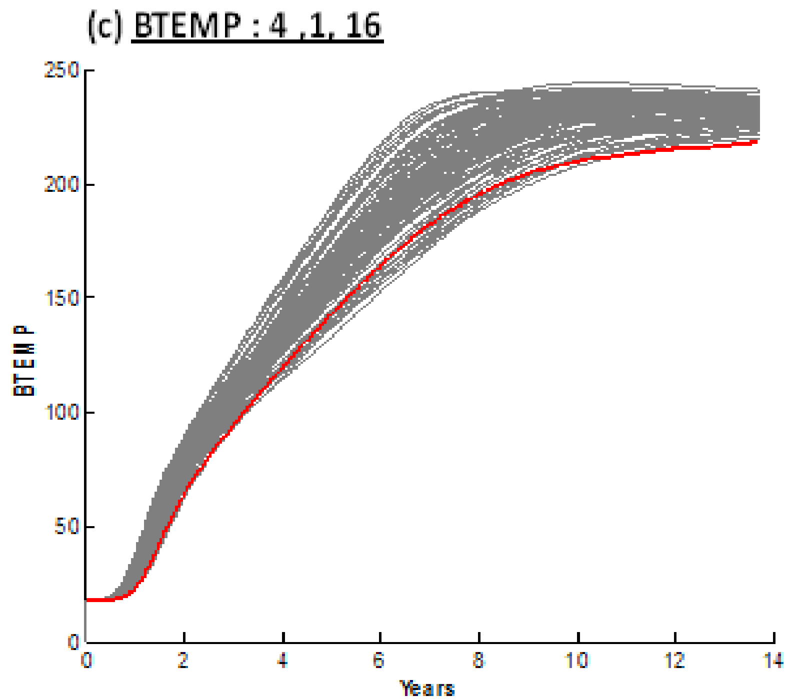
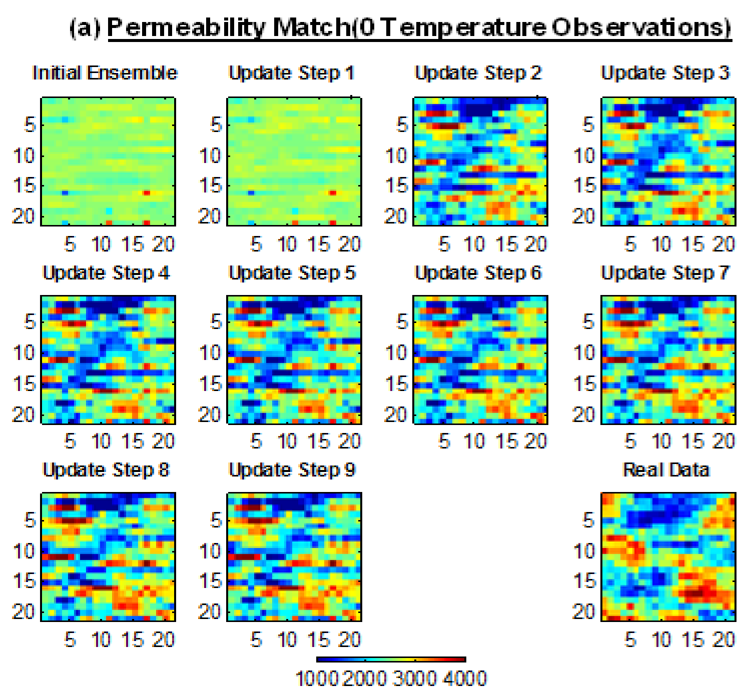


Figure 4.2: Initial Ensemble of production data forecasted using the reference permeability in simulation

The history matching was performed for 10 update steps, and the production data was assimilated at every three months. A measurement noise variance of 5, 0.01, and 1 were assigned to Q, cSOR, and the temperature observations, respectively. The permeability perturbation noise variance was chosen as $1.0e^{-2}$ for all grid block locations. The Root mean square errors (RMSE) for all the three cases are plotted to match determine the quality of the mismatched results. In order to investigate the importance of temperature observations in EnKF to reliably represent the uncertainty in prediction of steam chamber rise or length of steam fingers at the edge of steam chambers, we perform the EnKF with the same initial realizations but with 0, 4 and 8 temperature observations along with the production rate (Q) and cumulative steam-oil ratio (cSOR) observations.

4.2 Model Parameter Update

As discussed before, the model parameters include parameters such as permeability, porosity etc that are traditionally called static because they do not vary with time. However in our EnKF based dynamic history matching we have assumed permeability as the tuning parameter which gets updated with time and thus can change with time. The updated mean permeability (Figure 4.3) at each step of data assimilation is compared for the three cases with 0, 4, and 8 temperature updates.



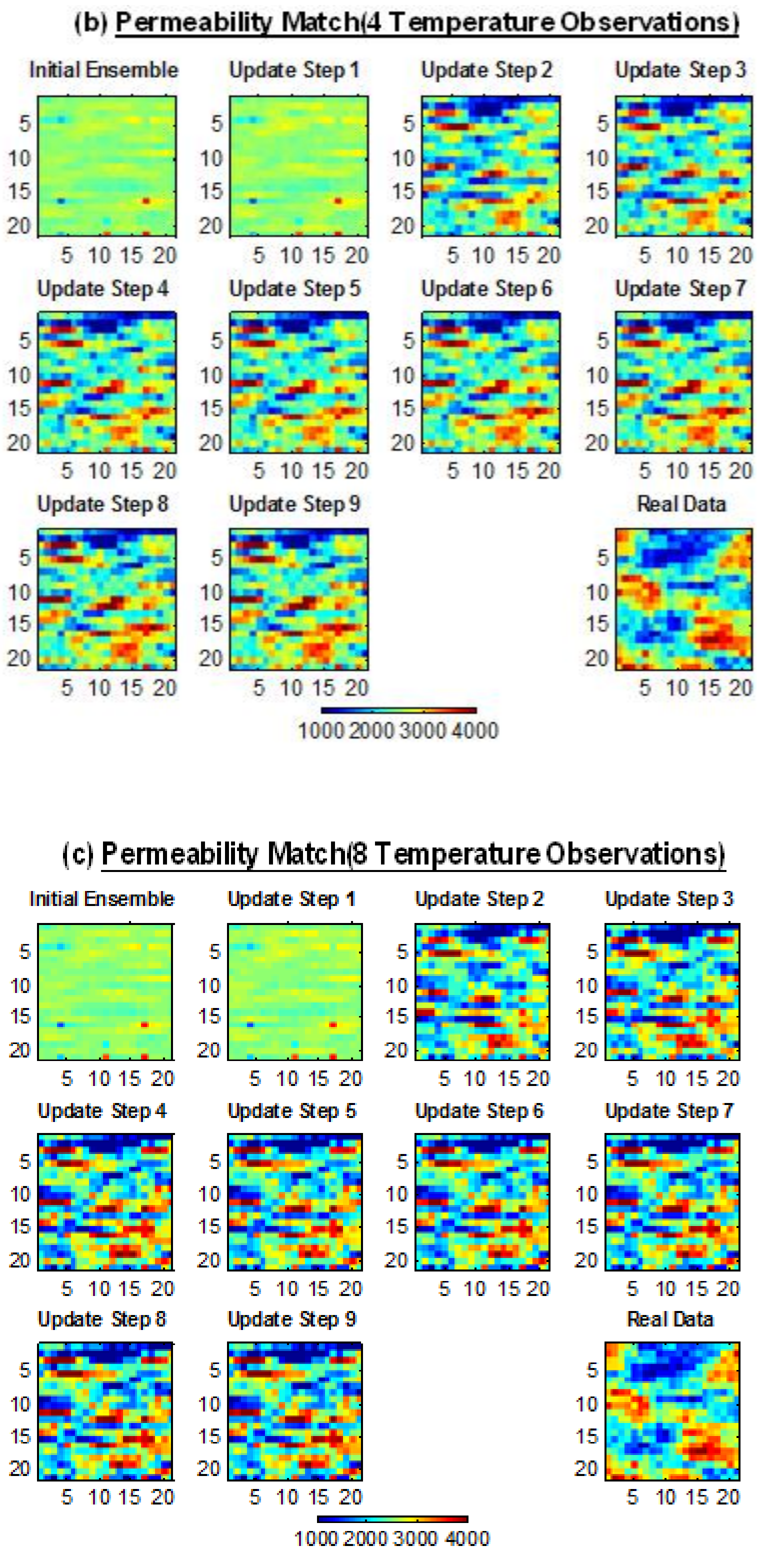


Figure 4.3: Comparison of the permeability update for the 3 cases with 0, 4 and 8 temperature observations. The average permeability map at different update steps compared to the true case is shown in each case

The true (benchmark) case is also shown in the bottom right of each figure for comparison. In each case, compared to the benchmark case, we can see that at the starting time when no production data is available, the averaged model is featureless with constant values close to the mean and variance of the input histogram. Also in the first few data assimilation steps, most variation in the averaged model is observed and we are able to successfully detect high and low permeability locations in the reference model with reduced uncertainty. As more and more production data is incorporated, improved average permeability models are obtained and the average permeability fields become closer to the benchmark case. However as compared to the initial data assimilation step, there is no major improvement in the permeability match and the averaged permeability fields become closer and closer between the different assimilation steps, clearly indicating that the early time production data contain valuable information about the reservoir heterogeneity.

In each case, it can be clearly seen that the updated mean permeability field has improved significantly and the final updated permeability predictions are close to the reference case. However, in the first single facies model, visually, it is difficult to compare the quality of permeability match in Figure 4.3.

4.3 Root Mean Square Error (RMSE)

RMSE is used to compare the quality of mismatched results. The Root mean square error (RMSE) is evaluated by calculating the difference between the estimated permeability field and the reference permeability field. For each gridblock, the RMSE for the entire ensemble of the updated realizations can be computed with the following formula:

$$RMSE_i = \sqrt{\frac{1}{N_e}\sum_{j=1}^{N_e}(y_{i,j} - y_i^{true})^2} \qquad (4.3.1)$$

Here $y_{i,j}$ is the estimated value of the permeability map for the i^{th} gridblock and j^{th} realization and y_i^{true} is the permeability value in the i^{th} gridblock of the reference field. Ne is the total number of realizations in the ensemble of model parameters. Finally the average RMSE is computed for all the gridblocks using the following formula:

$$Avg.RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RMSE_i)^2} \tag{4.3.2}$$

Here N is the total number of gridblocks. As more and more production data is incorporated in the data assimilation step, the RMSE and the Avg. RMSE values decreases and the ensemble of models move towards the benchmark case.

We have plotted the cumulative Avg. RMSE graph (Figure 4.4) for all the three cases with 0, 4 and 8 temperature observations to compare the quality of history-matched model.

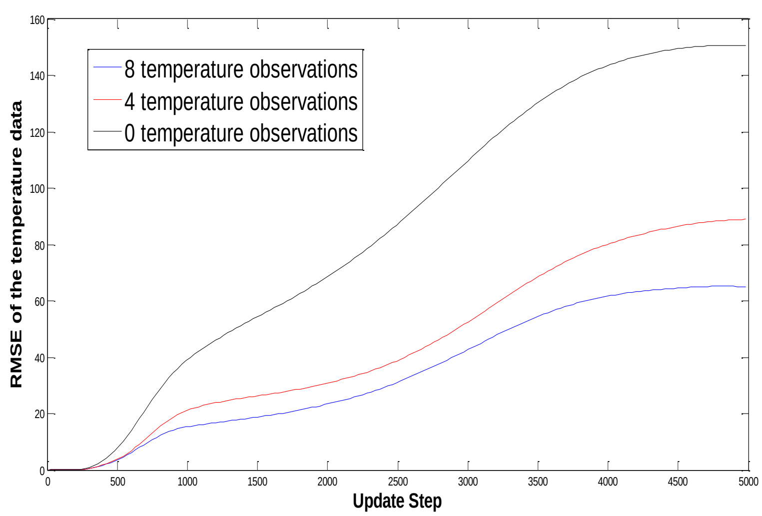


Figure 4.4: Single facies model, Comparison of Root mean square error value of the temperature data for the three cases

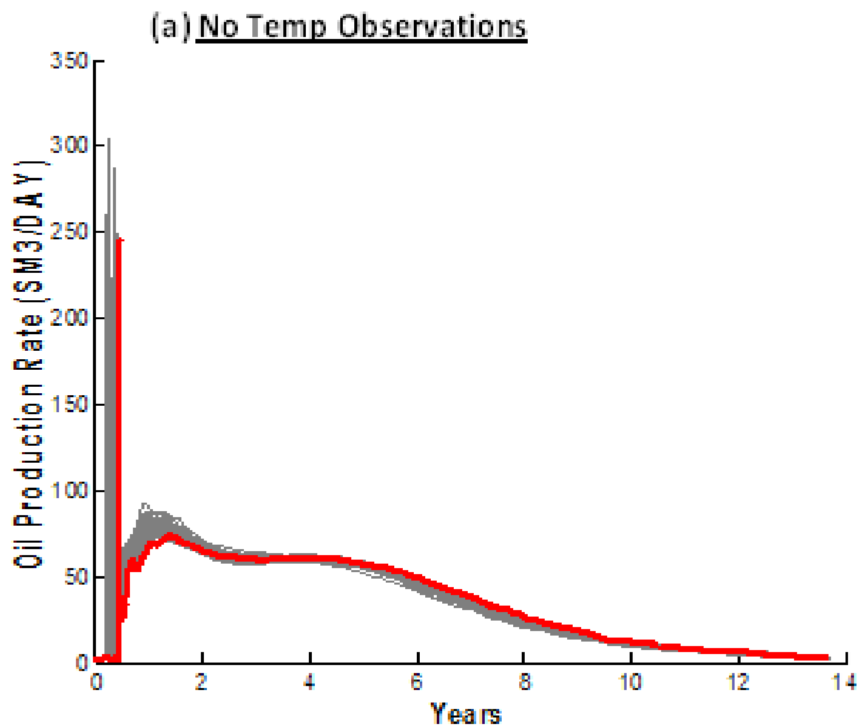
We randomly selected a block temperature data, which has not been updated during the data assimilation step. When 4 temperature observations are used, the RMSE values are drastically reduced, as compared to the RMSE values in cases with no temperature observations. However, including 8 temperature observations showed no major improvements, as compared to the case with 4 temperature observations. Thus, real-time temperature measurements for continuous model updating in SAGD reservoirs led to better reservoir heterogeneity predictions. However the RMSE results reveal that after the optimum number of sensors, further increasing the number of temperature observations showed no major improvements.

4.4 Dynamic Parameters Match

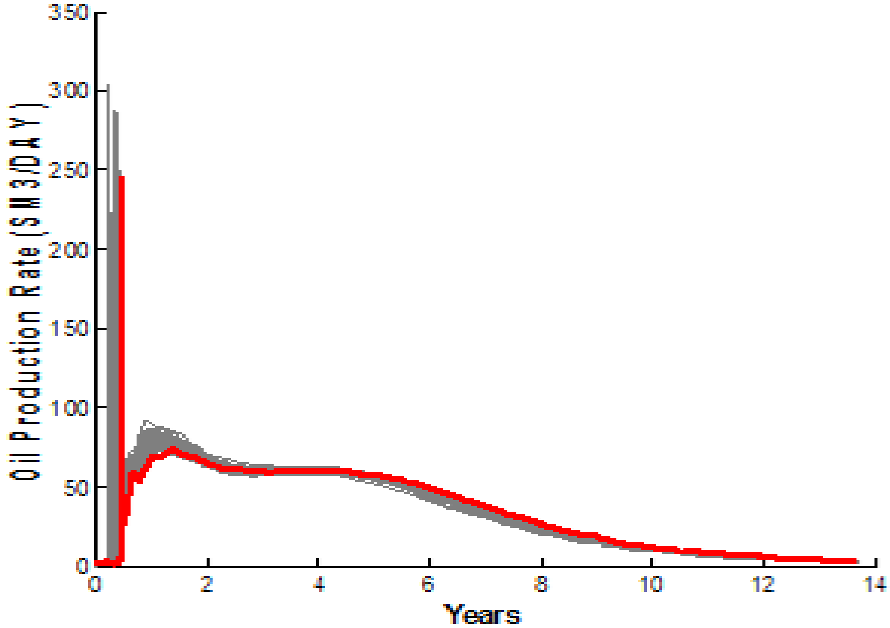
Using the updated permeability value in simulation, the ensemble of production rate, cumulative steam-oil ratio, and temperature data is plotted along with the true case (Figure 4.5 to Figure 4.7) to show the after history match predictions. As compared to the initial ensemble of production data (Figure 4.5) where all the predictions are far from the true case, the after history match predictions moved closer to the true case clearly indicating significant reduction in uncertainty of Q, cSOR, and temperature data after updating with the EnKF algorithm. All the realizations of the ensemble move closer to the true value, thus indicating improvements in predictions after history matching.

The red line in the figure represents the observations from the reference model and the grey lines represent the trajectories of the model predictions after re-running the updated models from initial time.

After History Match : Production Rate Match



(b) 4 Temp Observations



(c) 8 Temp Observations

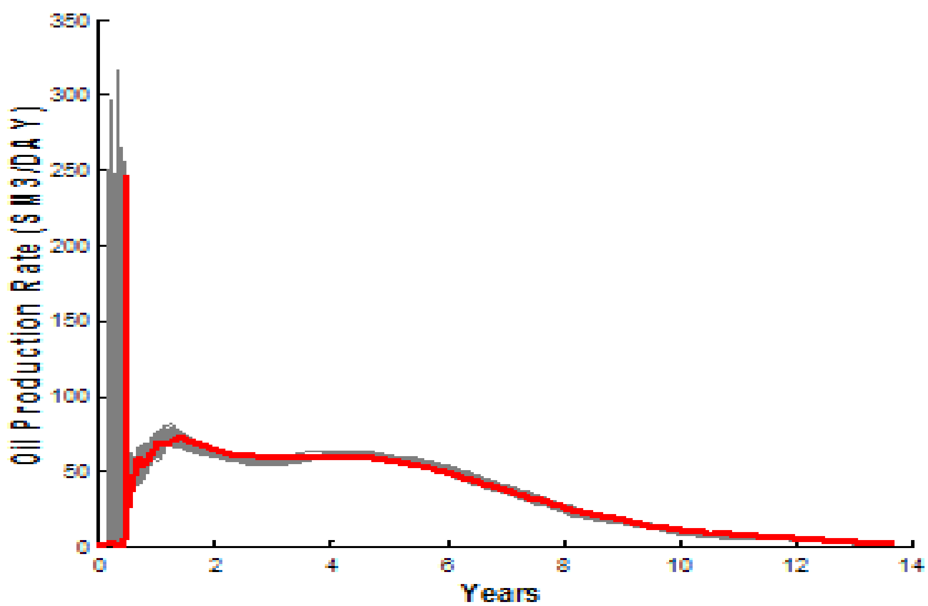
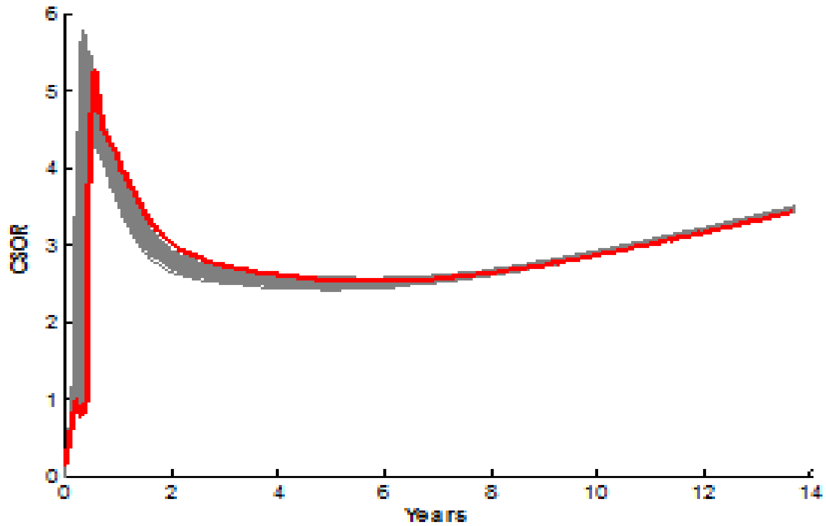


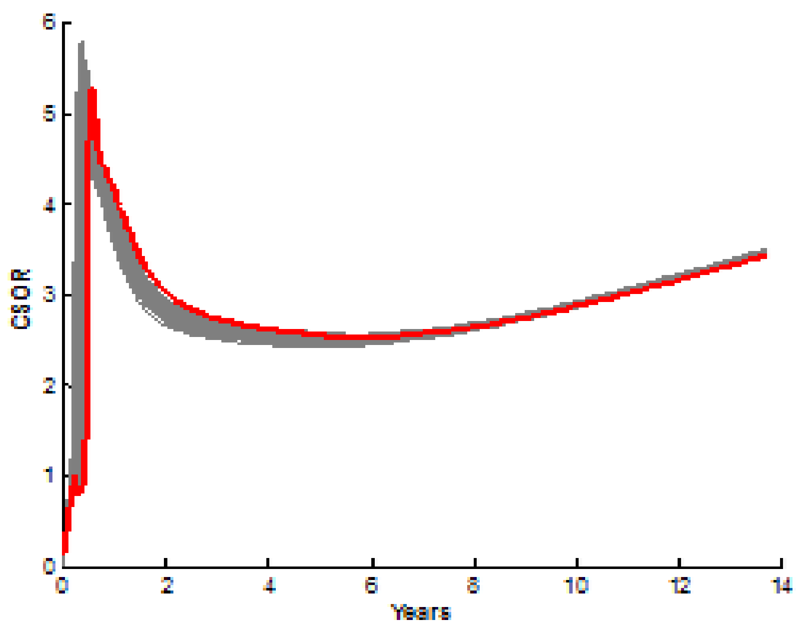
Figure 4.5: Oil production rate after history match for all the three cases with different temperature observations

After History Match : Cumulative Steam-Oil Ratio

(a) No Temp Observations



(b) 4 Temp Observations



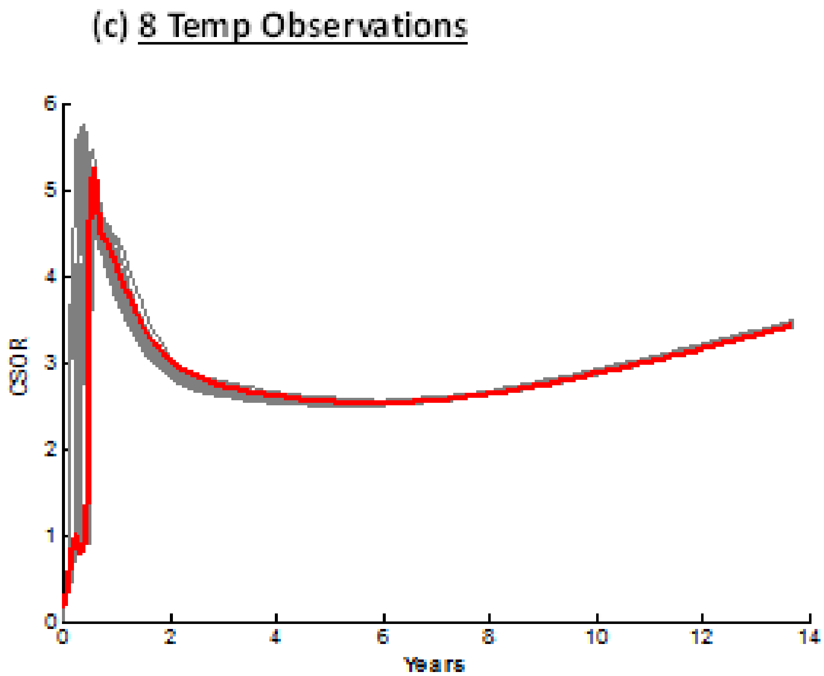
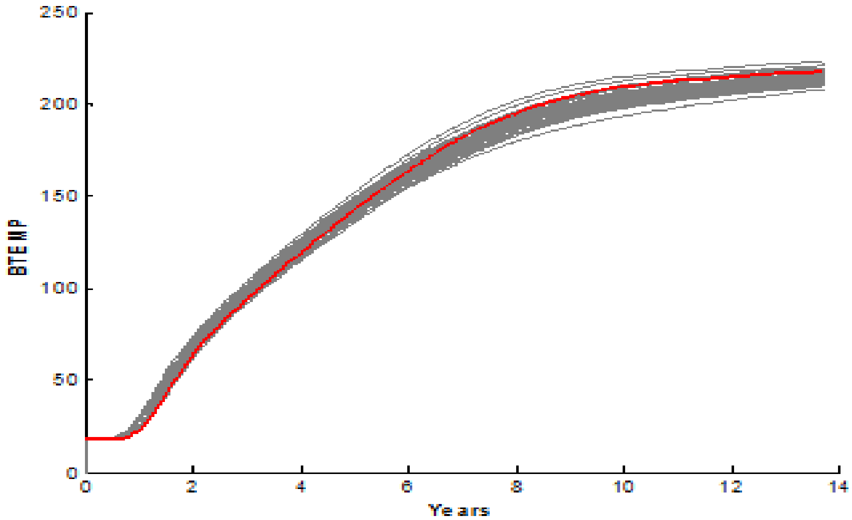


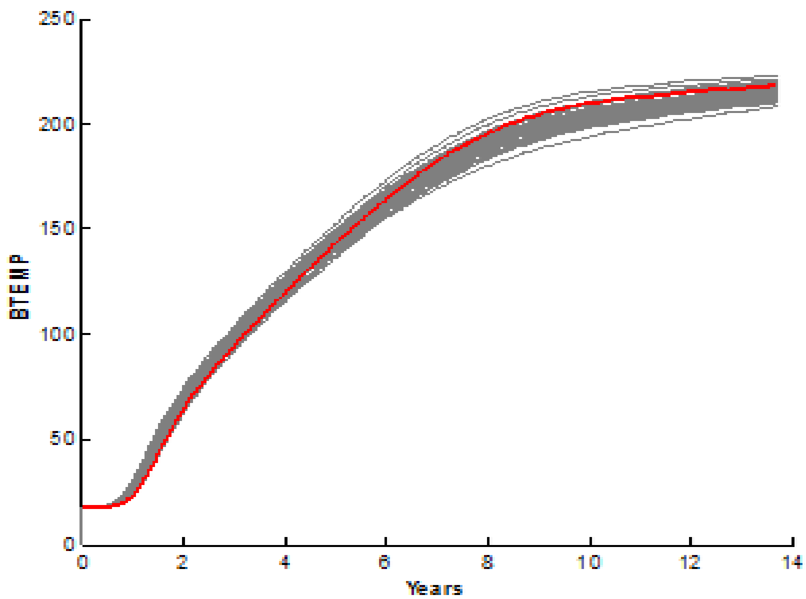
Figure 4.6: Cumulative steam-oil ratio after history match for all the three cases with different temperature observations

After History Match : Block Temperature

(a) No Temp Observations



(b) 4 Temp Observations



(c) 8 Temp Observations

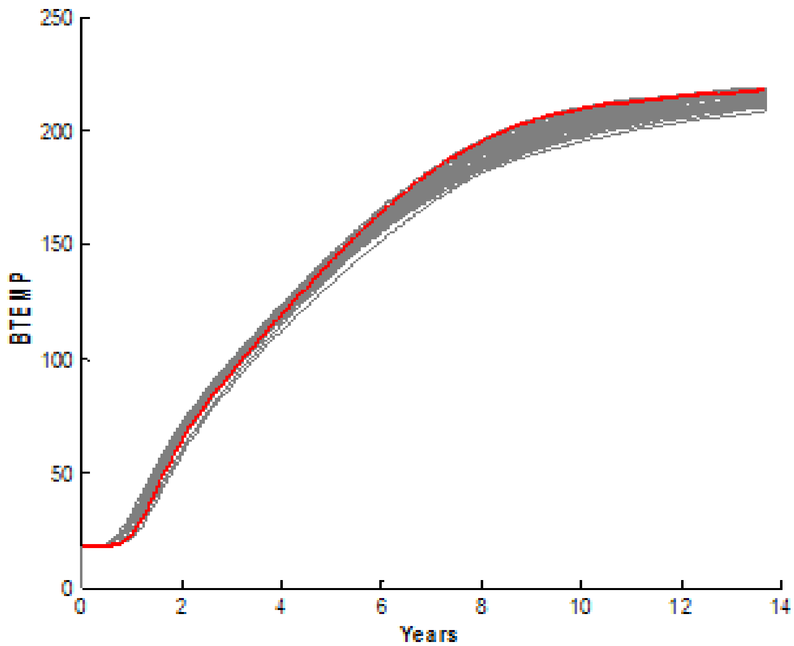


Figure 4.7: Block temperature after history match for all the three cases with different temperature observations

Chapter 5

Two-facies 2-Dimensional SAGD reservoir model updating using EnKF

The second case study has been done to investigate the application of the Ensemble Kalman Filter (EnKF) for detection of continuous shale barriers in SAGD reservoirs. The quantitative reservoir characterization of heterogeneity and determination of shale barriers are important for uncertainty assessment and prediction of production performance in SAGD reservoirs. This also aids in identifying the reservoir zones with the greatest SAGD potential and selecting the optimal number of SAGD wells for production. The shale barriers act as flow barriers depending on their size, location, and continuity throughout the reservoir. The long continuous shale barriers are important to characterize, as they are the barriers for steam migration which greatly influences the reservoir performance; however, the short horizontal shale barrier does not have much effect on the reservoir performance (Butler et al, 1992). In this chapter we will implement the EnKF methodology to history match and characterize a 2-D two facies SAGD reservoir model containing sand and shale facies. Similar to the previous case study, the EnKF algorithm was prepared in the MATLAB programming software by interfacing it with the Eclipse-E300 for compositional simulational modeling and Petrel RE for facies modeling. This case study consists of a two facies model in which the facies distribution is the unknown model parameter. Figure.5.1 (b) shows the benchmark facies distribution, which was generated using unconditional Sequential Indicator simulation (SIS) in Petrel. The reference field shale barriers, which we aim to detect by the EnKF algorithm, based on the real time production and temperature data.

2-D two facies- SAGD reservoir models, having 21x1x21 grid blocks with model dimensions of 250 meters x 750 meters x 35 meters, have been used in this case study. A pair of injector and producer is used in the simulation model. The observation data includes the oil production rate (Q), cumulative steam-oil ratio (cSOR), and temperature data from different sensor locations. The porosity is assumed to be a constant 35% value throughout the reservoir. The other reservoir parameters are presented in Table (5.1)

Table: 5.1 Two facies SAGD Model Reservoir Properties

Model Dimensions	21 x 1 x 21
Length in X,Y,Z direction	250 m x 750m x 35m
Porosity	35%
Permeability Range	Sand - 3000md; Shale - 50md
Formation Heat Capacity	7.4E2 KJ/m3/K
Rock thermal Conductivities	2.1E2 KJ/m/day/C
Temperature	18 C

No. Of wells	1 producer & 1 injector
Pressure	30 Bar
Facies Proportion	60 % Sand 40 % Shale
Injected Fluid	Steam
Steam Quality	90%
Injection Temperature	285 C

5.1 Parameterization with Discrete Cosine Transform

The EnKF is a Monte-Carlo based technique that only uses the mean and covariance of the prior probability density function (pdf) when calculating the posterior ensemble. It is based on the simple assumption of Gaussianity. Thus in highly non-linear problems, the traditional EnKF incorrectly estimates the uncertainty and fails to obtain a good production data match. This problem arises with multiphase flow and non-Gaussian distributions. All these problems requires the need to make improvements in the traditional EnKF method to update and history match the reservoir models whose petrophysical properties are not necessarily Gaussian (Evensen 2007, Aanonsen et al, 2009). The shale barriers in a SAGD reservoir, due to its complex geological nature, are exhibited as a different facies and thus it is difficult to detect shale barriers using the traditional EnKF algorithm. Different approaches has been used to model non-

Gaussian parameters such as Discrete Cosine Transform, Truncated Pluri-Gaussian and Gaussian Mixture models (Evensen, 2007).

The Discrete Cosine transform is a Fourier based transformation applied to decompose the spatial distribution of the facies indicators into the coefficients of the retained cosine basis functions. DCT is performed on each realization of the initial ensemble and certain number of basis functions and the coefficients are retained. It is noted that the total number of basis functions (r) can be much less than the total number of model parameters. The DCT coefficients are incorporated into the state vector instead of the model parameters (m). After the EnKF update step, inverse DCT transform is used to convert back the updated DCT coefficients into facies indicator values. These updated indicators are further used in the subsequent forecast and update steps as new observations become available.

5.2 Generation of Initial Ensemble

The two-facies 2-D model has shale and sand distributions whose permeability is assumed to be uniform with an average value. The permeability of sand and shale is set to 2000 md and 50 md. The reference facies distribution is generated through the Sequential Indicator simulation (SIS) technique using Petrel RE by assuming an exponential variogram model with a range of 150 m and 100m in the major and minor direction respectively, along an azimuth angle of 135^{o}. For the reference case, the facies proportion is 60% sand and 40% shale. The reference reservoir model. Figure 5.1(b) has continuous shale barriers which we aim to detect combining a novel parameterization approach, the discrete cosine transform (DCT) with the Ensemble Kalman Filter. Similar to the previous case, at the starting time, (t=0) when no production data is available we can see that the initial averaged model. Figure. 5.1(a) is featureless and has constant values which are very close to the mean and variance of the input histogram. The simulated dynamic data, such as Q, cSOR, and temperature observations, that is obtained using the reference case are considered as true case and are assumed to be available at the end of every month. To evaluate the performance of the SAGD process by using temperature observations as dynamic parameter updates in EnKF, we run three cases with 0, 4 and 8 temperature observations.

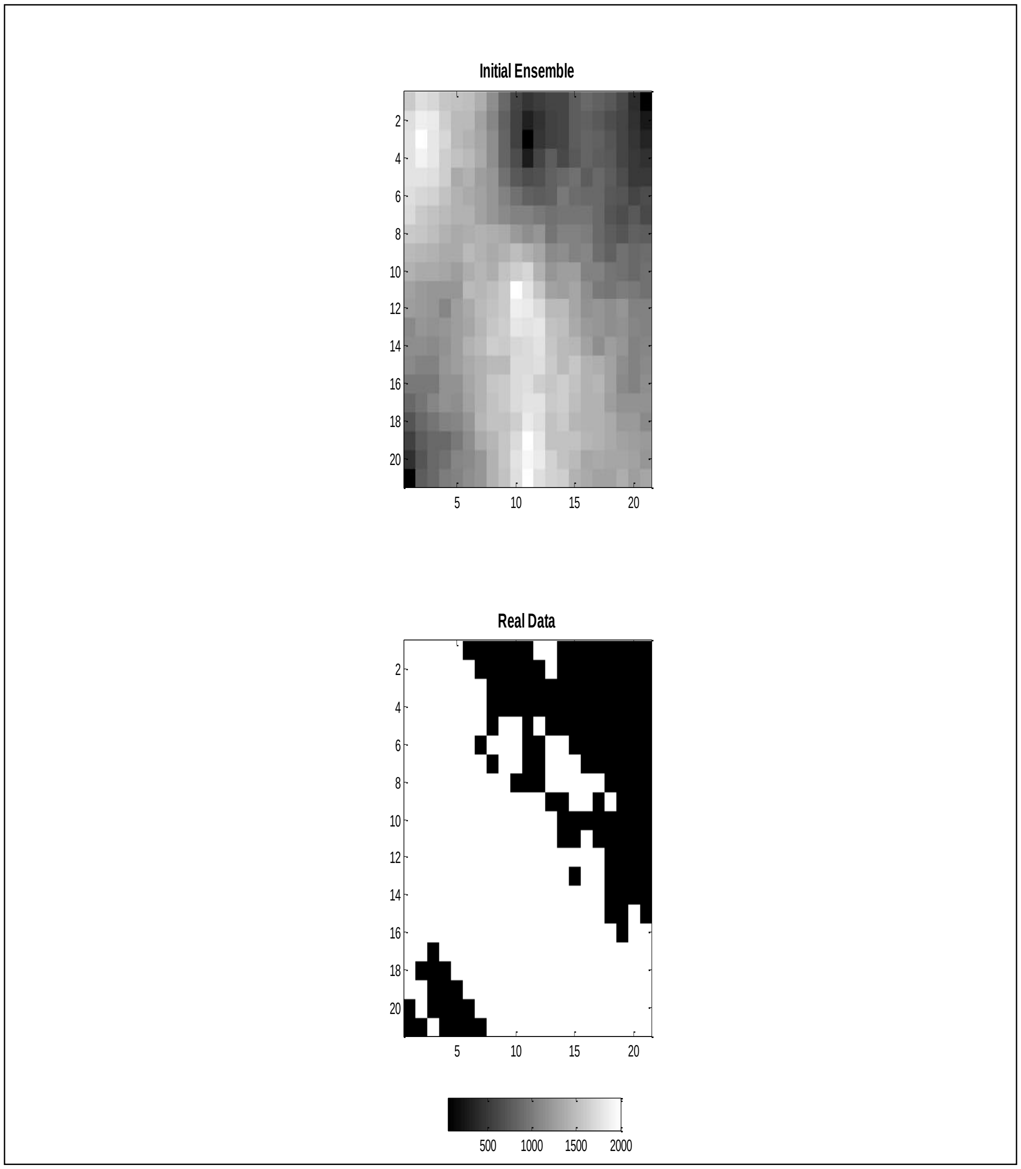
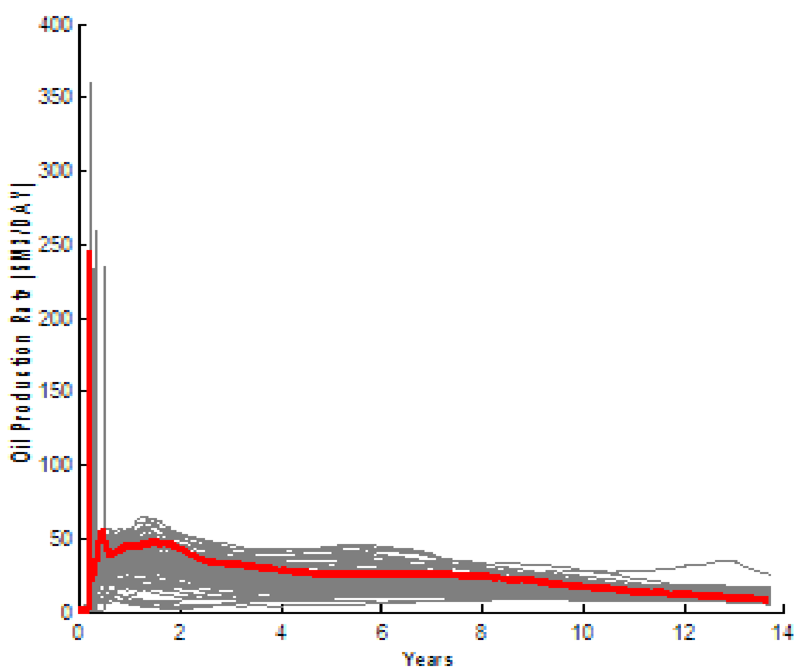


Figure 5.1: Two facies model
Top: Average of initial ensembles of 2-facie model
Bottom: Benchmark case facies distribution

Using the reference facies distribution, an ensemble of 100 distributions were generated via the sequential indicator simulation method. This ensemble of facies models is the input for the EnKF algorithm and is updated at the end of every 3 months, thus assimilating the most current data. We have used the discrete cosine transform (DCT) to parameterize the facies indicators whose coefficients are then included in the state vector and updated. The hard facies data is assumed to be available at the (5,1,4), (17,1,4), (5,1,18), and (17,1,18) grid blocks and the well locations. These hard data are used as conditioning data.

Before History match

(a)Production Rate



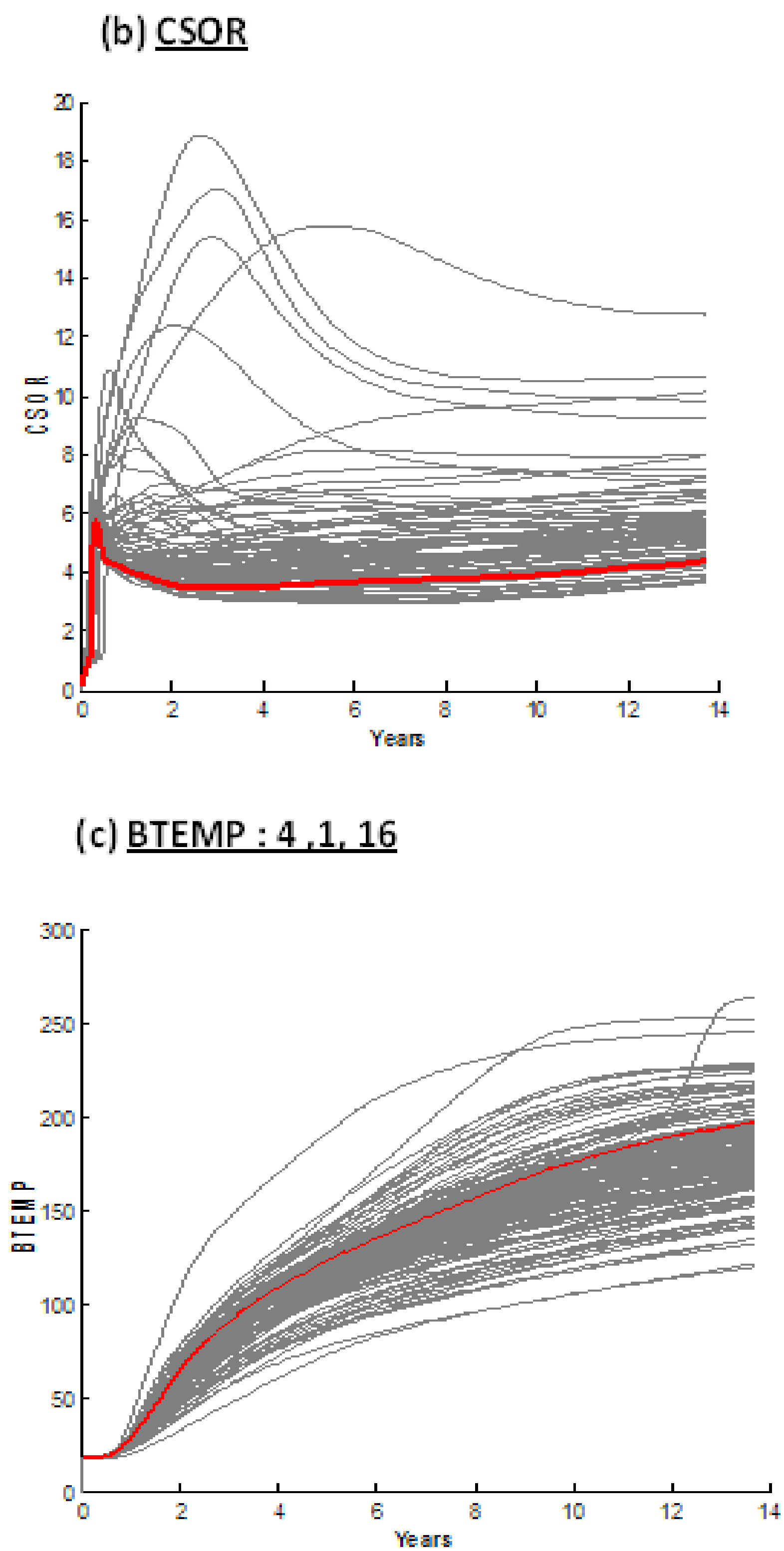


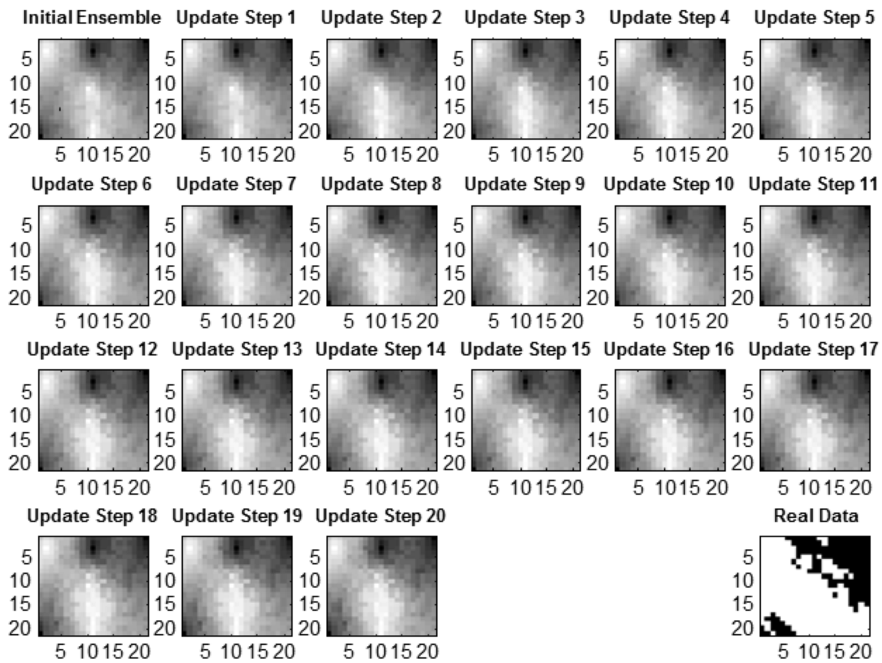
Figure 5.2: Initial Ensemble of production data forecasted using the reference facies distribution in simulation

The history matching was performed for 21 update steps for the 2-D model, assimilating the production data at the end of every three months. The same measurement noise variance as the previous case was assigned to Q, cSOR, and the temperature observations. The model noise variance was chosen as $1.0e^{-2}$ for all the grid blocks. Again, three different cases with 0, 4, and 8 temperature observations have been run for the 2-D model with the same set of initial realizations. Simiar to the previous case study, the Root Mean Square Error (RMSE) value for all these cases has been plotted to compare the quality of final updated facies model.

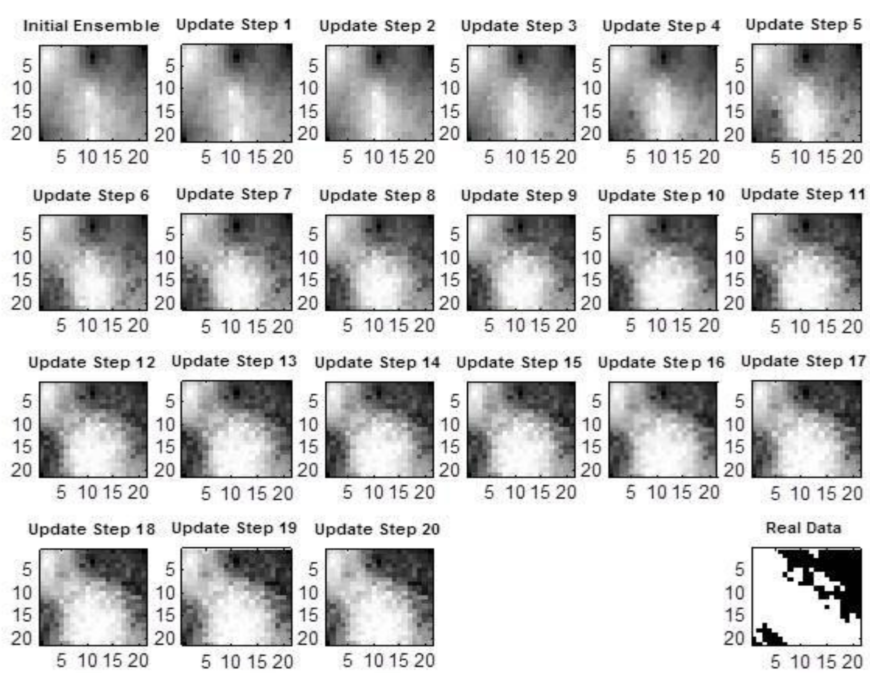
5.3 Model Parameter Update

For model parameter estimation in two-facies SAGD reservoirs, a comparative study was carried out to examine the importance of temperature data inclusion in the data assimilation step during EnKF assisted history matching process. After applying the DCT + EnKF to perform history matching of a two-facies, the updated mean facies for each case is shown in Figure 5.3. It can be clearly seen that in the first case, in which temperature observations are not used for history matching, the facies update is underestimated, and even after 21 update steps, the final model is not able to catch the shale barriers within the reservoir. However, when temperature observations are included, the facies match is close to the reference case and results in improved shale barrier detection.

Facies Match (0 temperature observations)



Facies Match (4 temperature observations)



Facies Match (8 temperature observations)

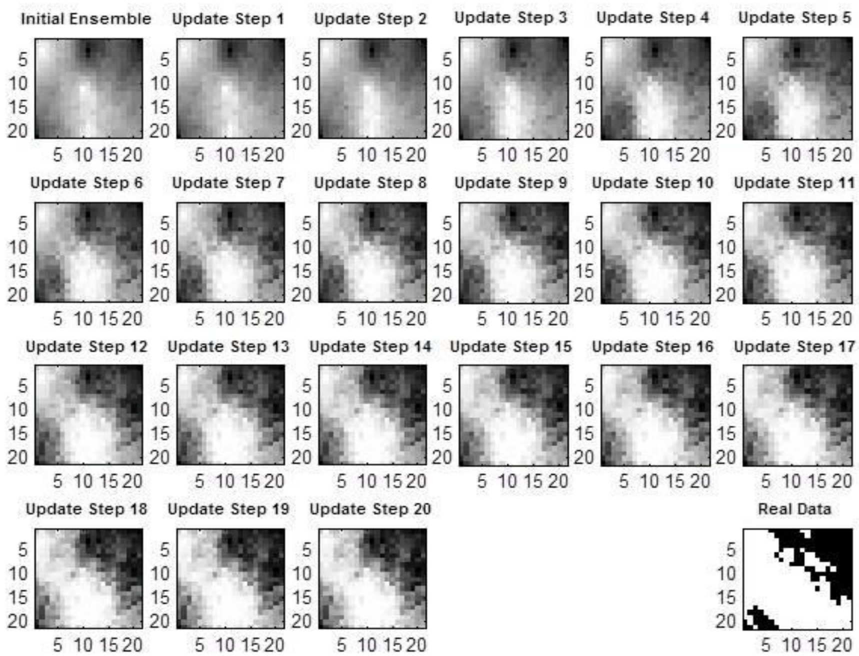


Figure 5.3: Comparison of the facies match for the three cases with 0,4 and 8 temperature observations. The average facies match at different update steps compared to the true case is shown in each case

Again similar to the previous case, the Root Mean Square Error (RMSE) plot is used to evaluate the quality of the final updated facies distribution at the end of the history matching.

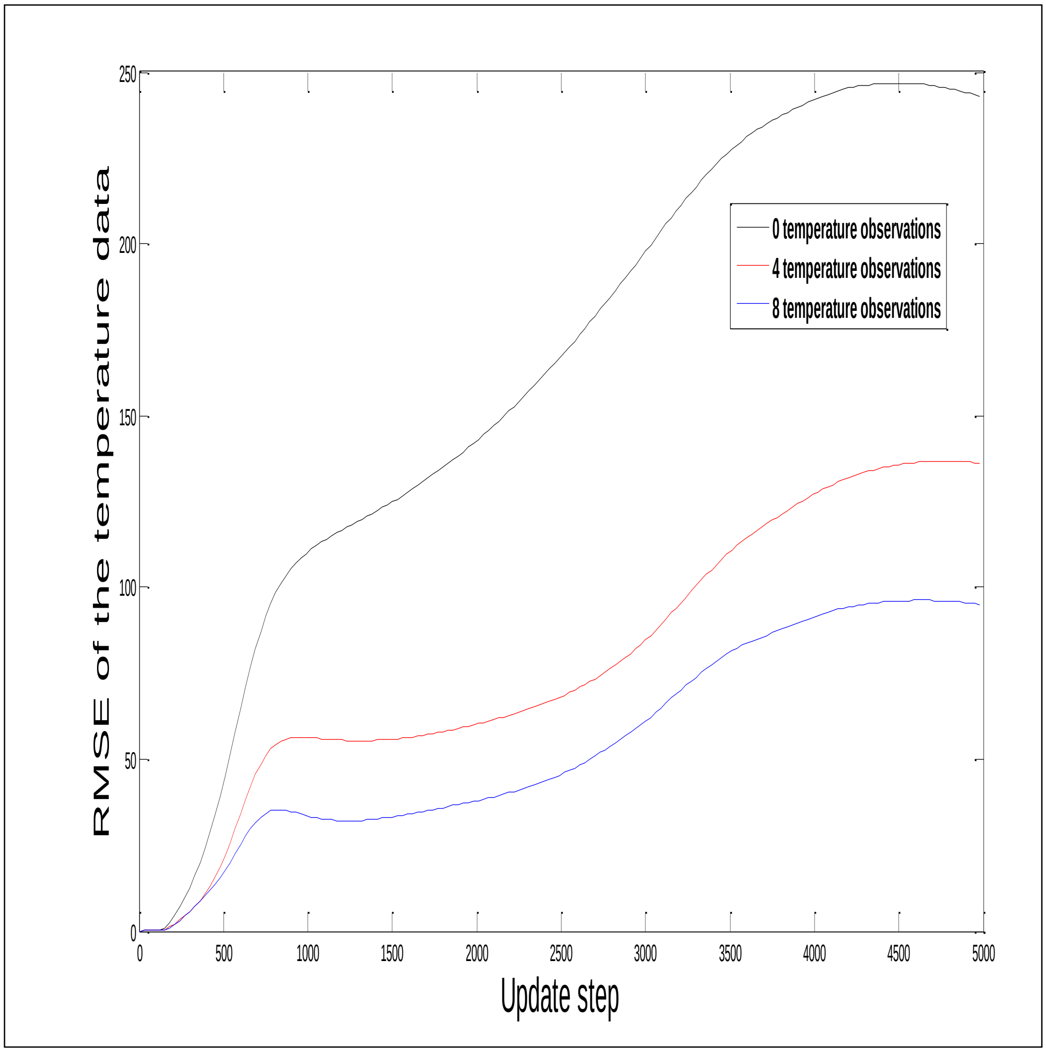


Figure 5.4: Two facies model, Comparison of Root mean square error value of the temperature data for the three cases

It can be clearly seen from Figure 5.4 that the inclusion of temperature observations in data assimilation step clearly gave reduced RMSE values as compared to the case when no temperature observations are used. However similar to the previous case, using more temperature observations showed no major improvements clearly indicating the need of using optimum number of temperature observations.

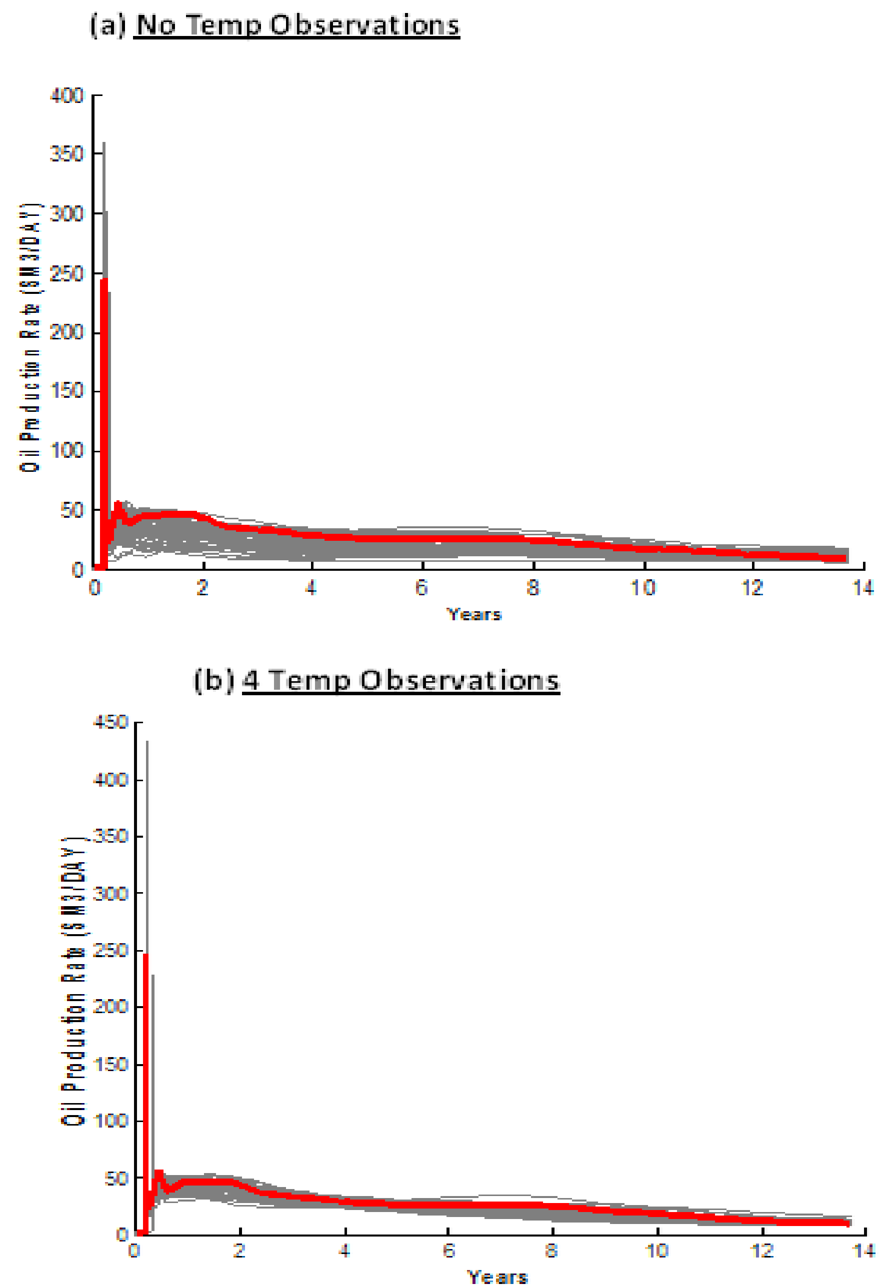
5.4 Dynamic Parameters Match

The history match results of production parameters for the two-facies 2D SAGD model are shown in Figure 5.5 to Figure 5.7 where oil production rate (Q), Cumulative steam oil ratio (cSOR) and temperature observations are plotted . The updated facies distribution is used in simulation to obtain the after history match ensemble. Clearly, the combination of EnKF and DCT is able to estimate the facies proportions that result in predictions matching the reservoir history more closely, as temperature observations are included for continuous model updating in SAGD reservoirs.

The redline curve represents the benchmark case results using the benchmark facies distribution in simulation, whereas the grey lines represent the 100 ensemble members prediction results using the final updated facies values in simulation. In each figure it can be seen that when temperature observations are not used, even after 21 update steps the ensemble members are far from the true case clearly indicating lots of uncertainty in the Q, cSOR and temperature data.

However when temperature observations are used, all the ensemble members move closer to the observations and uncertainty is significantly reduced.

After History Match : Production Rate Match



(c) 8 Temp Observations

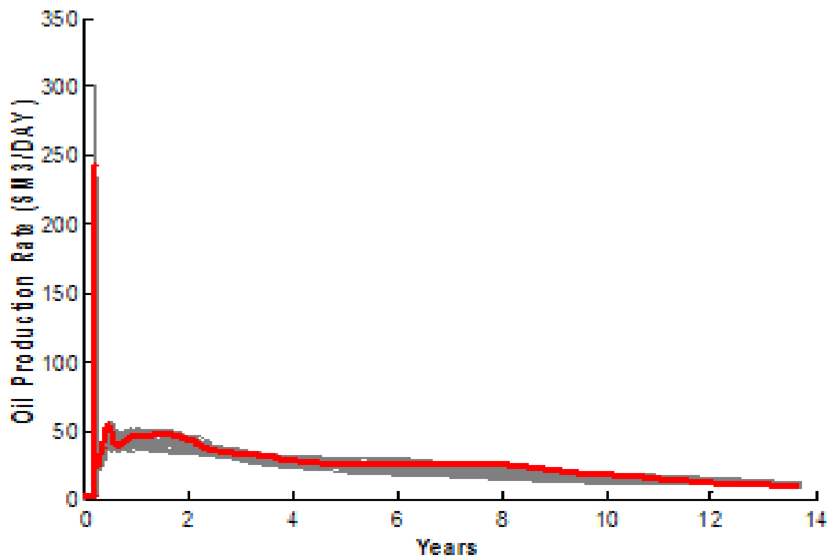
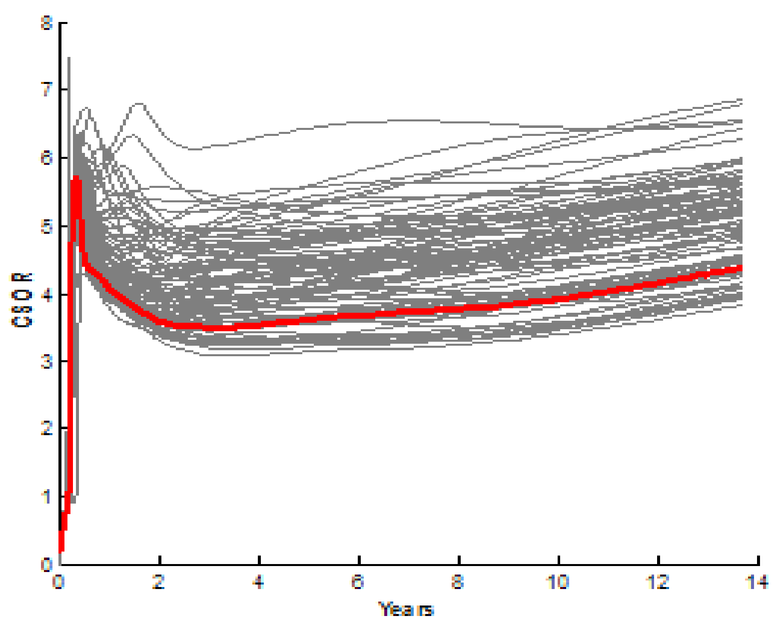


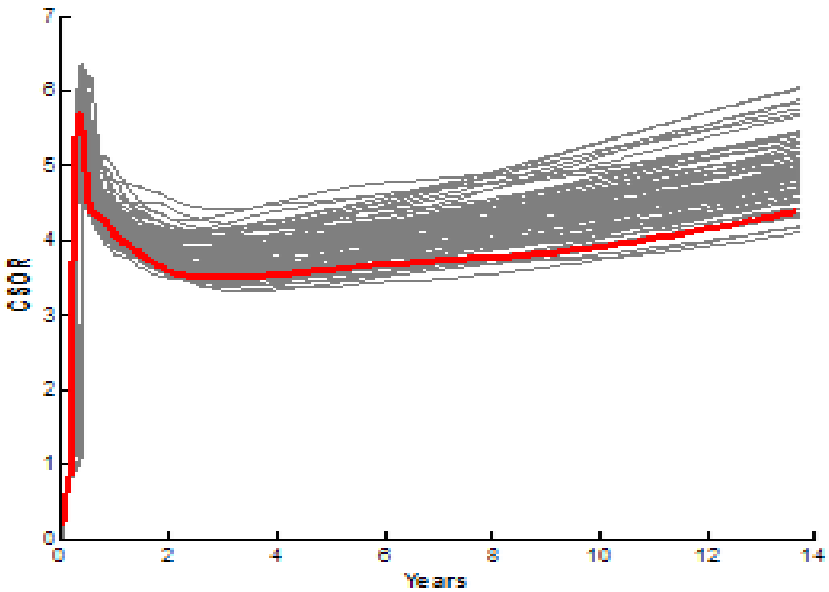
Figure 5.5: Oil Production rate (SM3/DAY) after history match for all the three cases with different temperature observations

After History Match : Cumulative Steam-Oil Ratio

(a) No Temp Observations



(b) 4 Temp Observations



(c) 8 Temp Observations

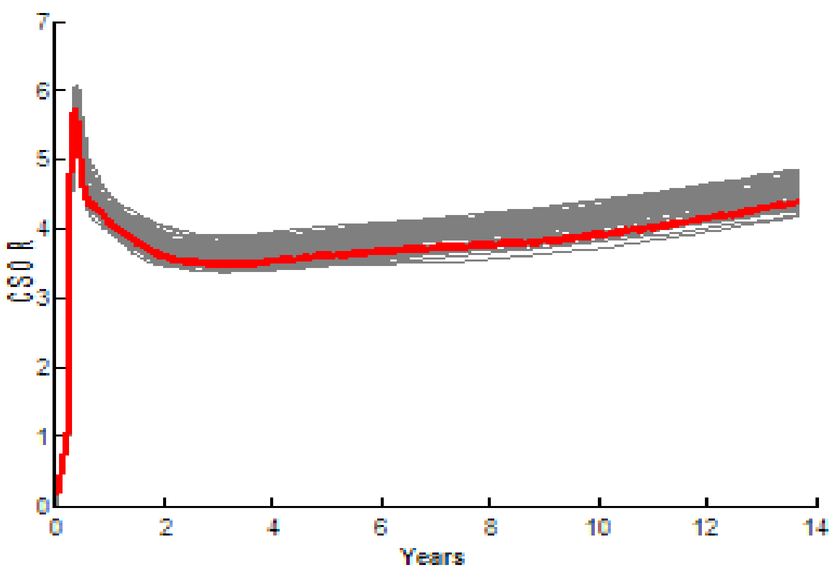
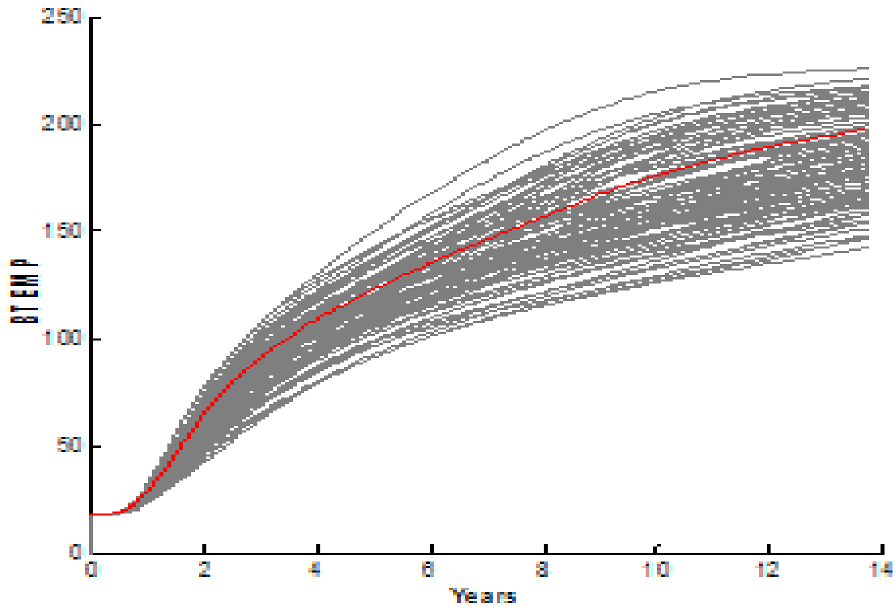


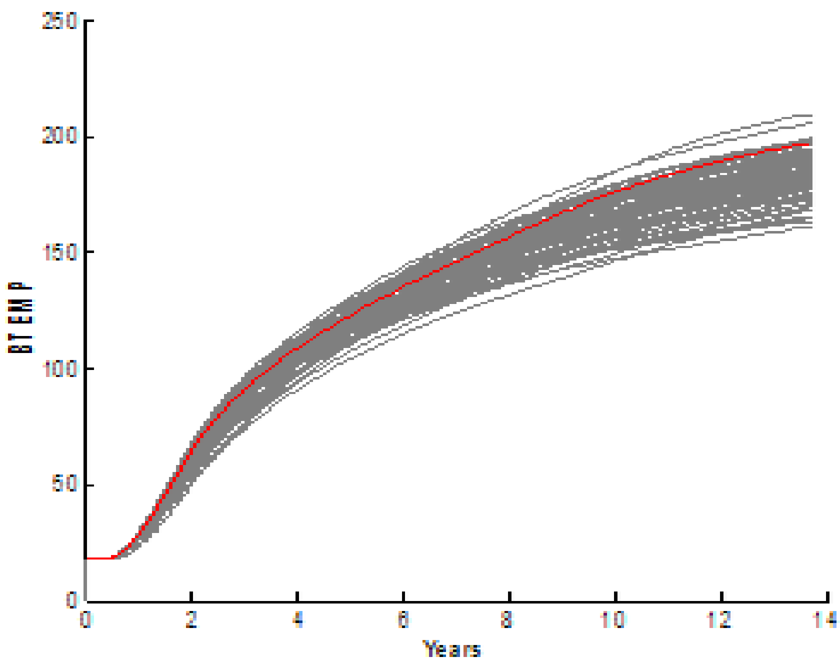
Figure 5.6: Cumulative steam-oil ratio after history match for all the three cases with different temperature observations

After History Match : Block Temperature

(a) No Temp Observations



(b) 4 Temp Observations



(c) 8 Temp Observations

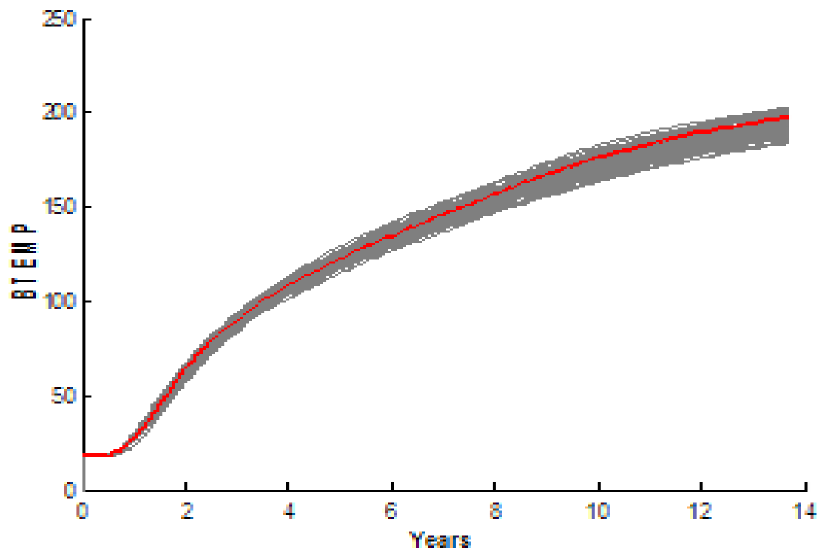


Figure 5.7: Block temperature after history match for all the three cases with different temperature observations

The distribution of steam chamber growth has also been compared for the true, initial, and updated facies distribution for all the three cases in Figure 5.8 and Figure 5.9 for the 2-faceis model. It is evident from the figure that inclusion of the DTS data for continuous model updating has great potential in providing a better understanding of the steam chamber growth and steam chamber orientation within SAGD reservoirs. Accurate information about the location and movement of steam chamber can be derived from the updated ensemble model with lower uncertainty.

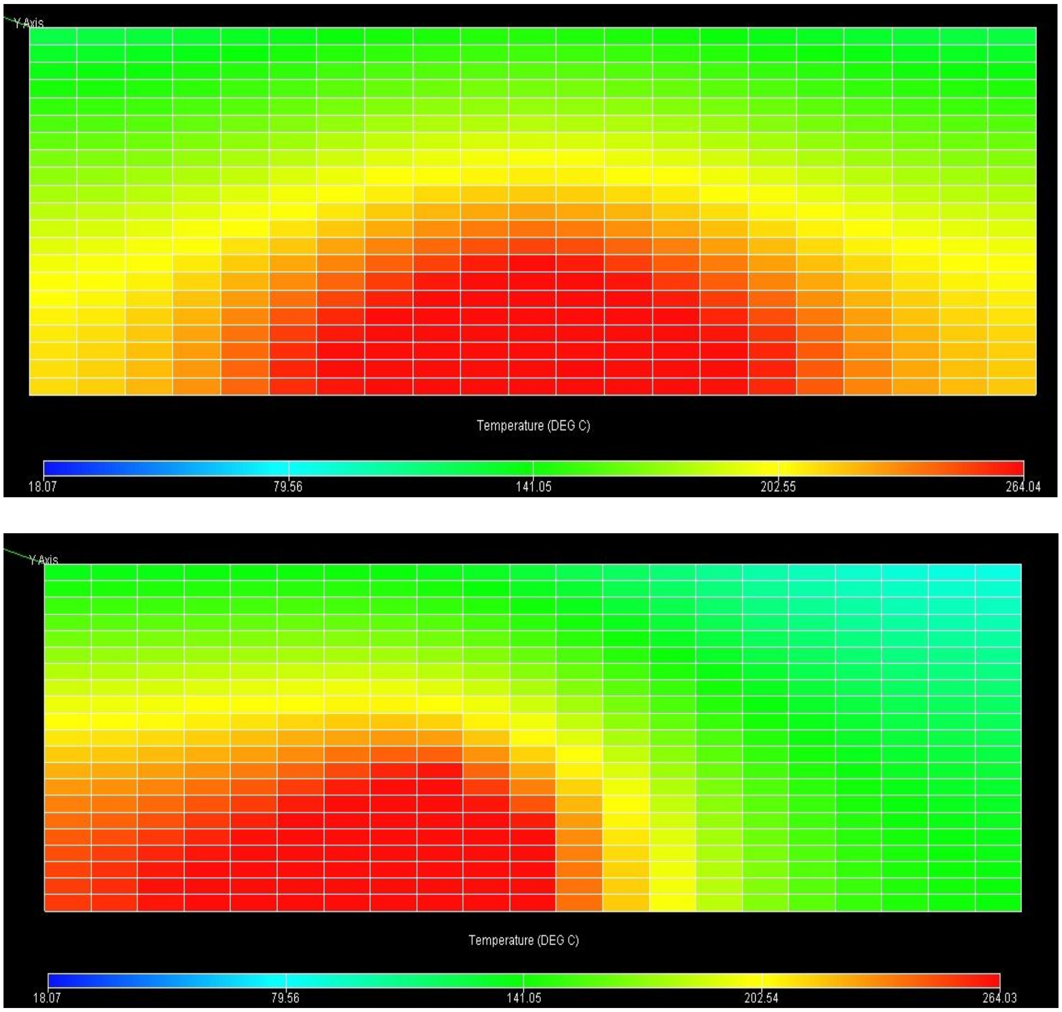


Figure 5.8: SAGD Model Temperature profile
Benchmark Case
Initial Ensemble Model

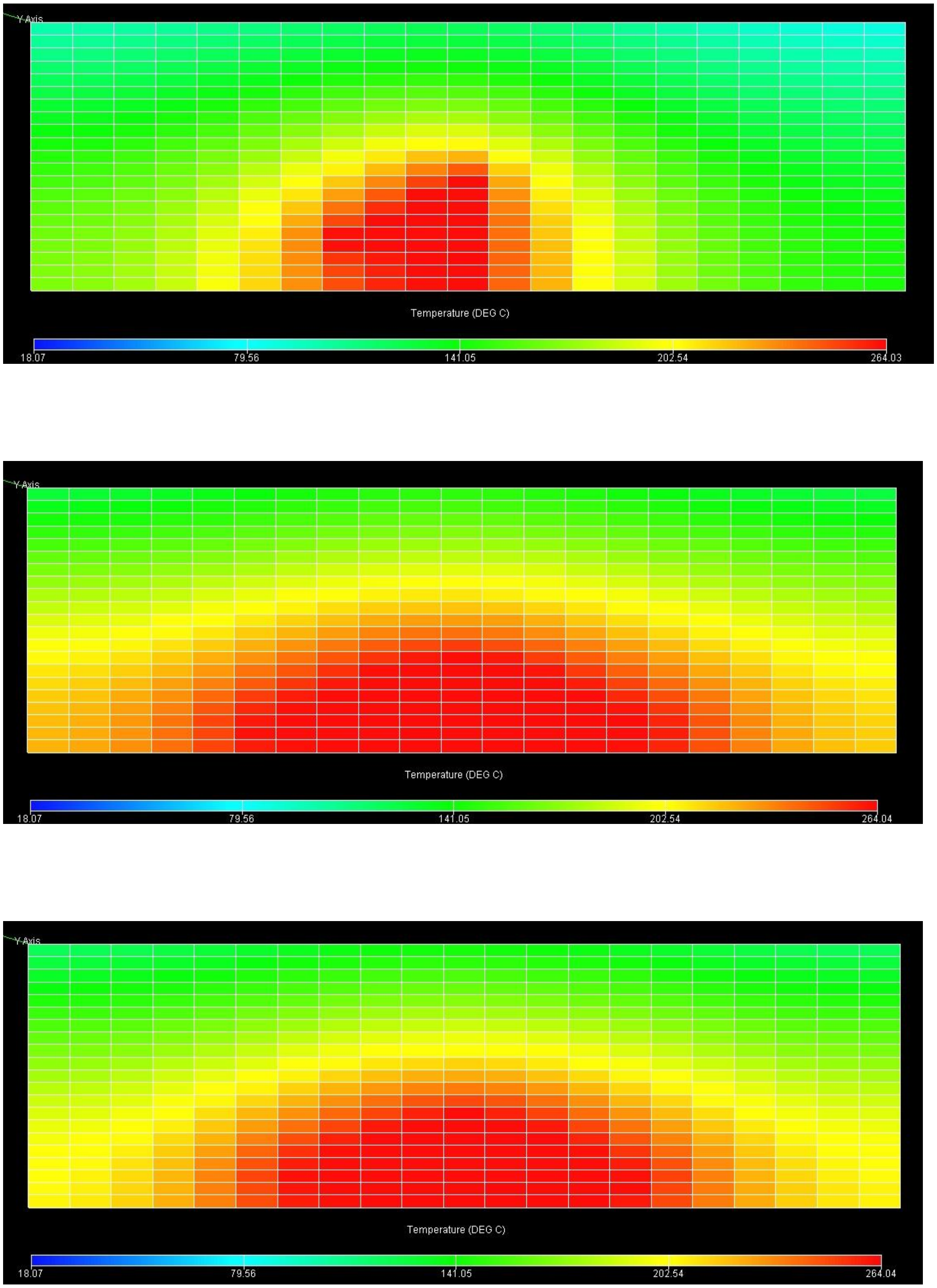


Figure 5.9: SAGD Model Temperature profile
(a) 0 temperature observations
(b) 4 temperature observations
(c) 8 temperature observations

5.5 Analysis to obtain optimum location of DTS data

An analysis is also done to obtain optimum locations of the four temperature observations for improved facies detection and reservoir characterization. In the first case, the four temperature observations (Figure 5.10a) are placed in one corner at (19,1,2) , (19,1,3), (20,1,2) and (20,1,3), whereas, in the second case, each temperature observation (Figure 5.10b)is kept close to a corner at (2,1,2), (2,1,20),(20,1,2), and (20,1,20). Finally, a third case is ran in which the temperature observations Figure 5.10c) are distributed within the steam chamber at (4,1,16), (4,1,10), (18,1,10), and (18,1,16).

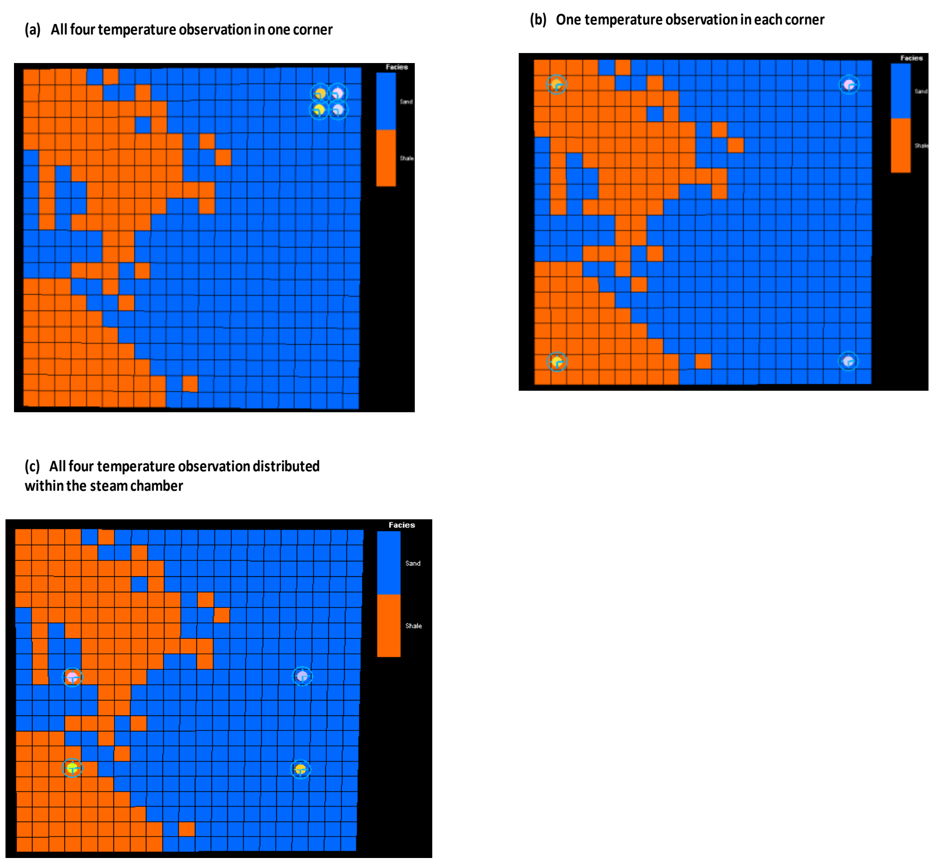
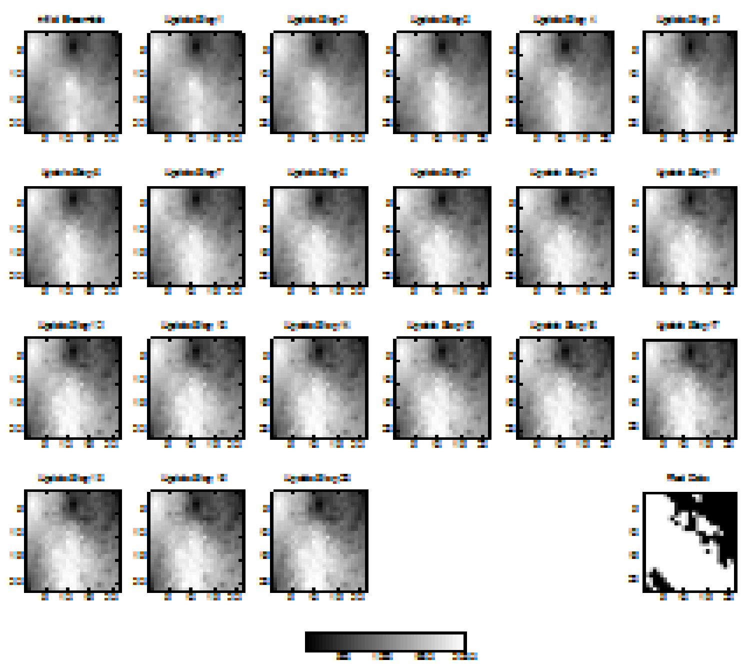


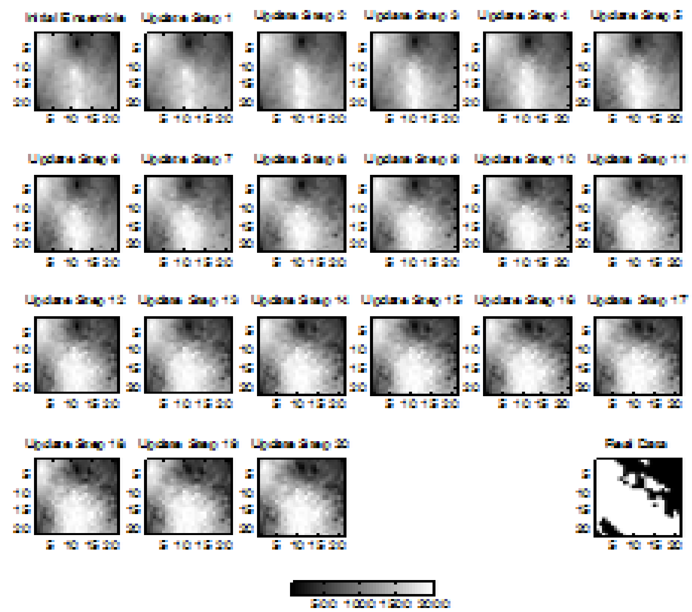
Figure 5.10: Different locations of 4 temperature observations for sensitivity analysis.

To compare the quality of mismatch in all the three cases, the mean facies match at each update step against the benchmark case is plotted. It is evident from the figure (Figure5.11) that inclusion of temperature observations, which are distributed uniformly within the steam chamber; provide a better facies match, as compared to the other two cases. The RMSE graph (Figure 5.12) of each case is plotted, which again shows the lowest RMSE for the case in which the temperature observations provides better information about the steam chamber propagation.

(a) Facies Match(all temp obs in one corner)



(b) Facies Match(one temp obs in each corner)



(c) Facies Match(temp obs distributed within the steam chamber)

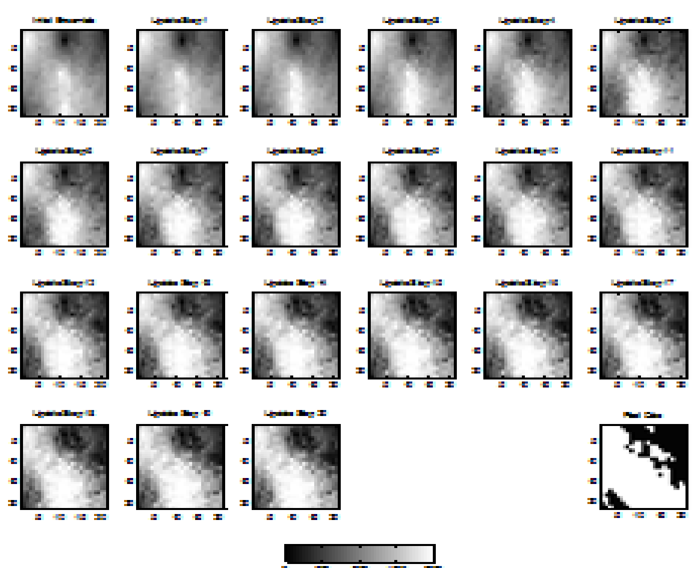


Figure 5.11: Comparison of facies match for three cases with different locations of 4 temperature observations. The facies map at different update steps compared to the benchmark case is shown in each case.

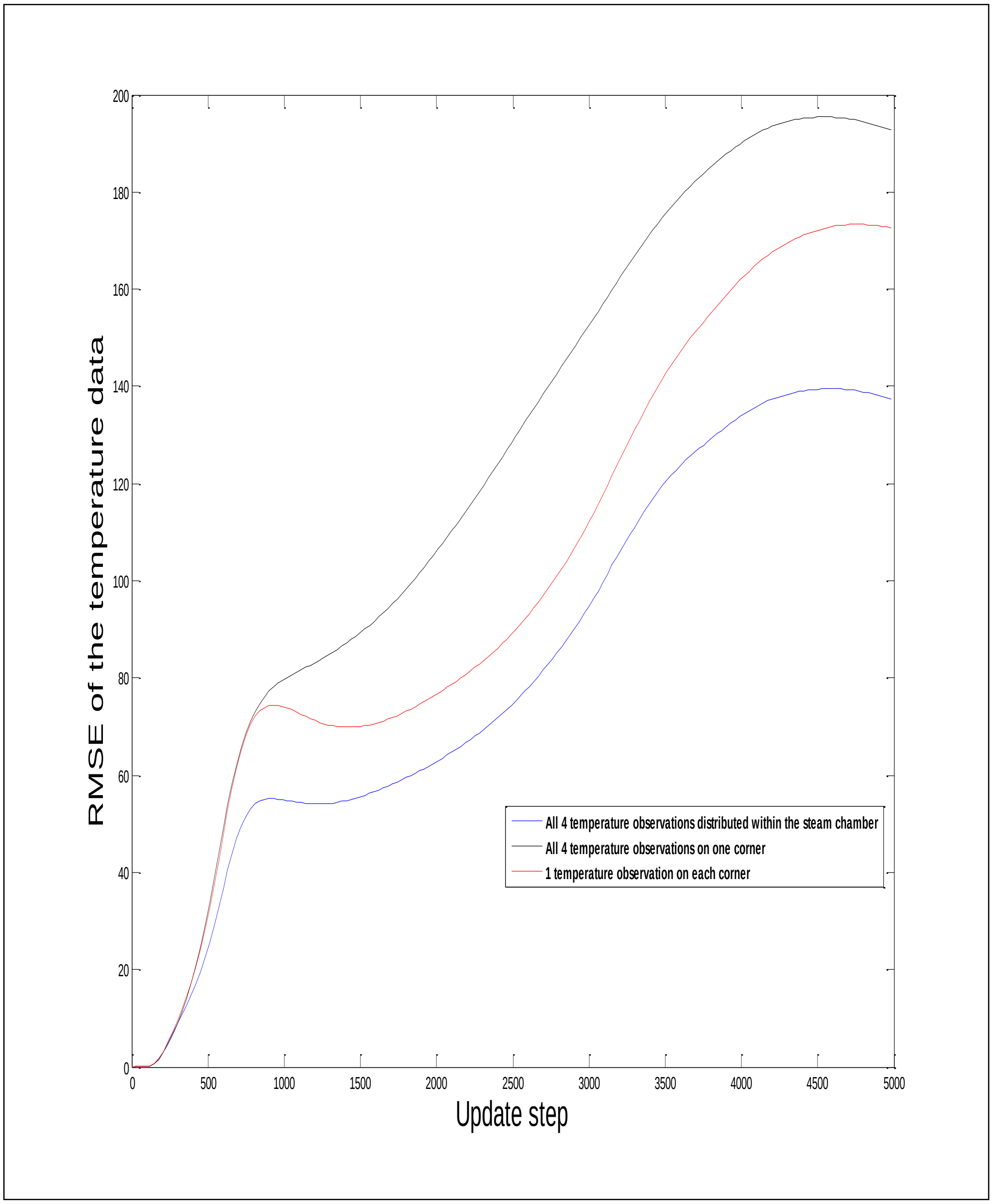


Figure 5.12: Comparison of Root mean square error value (two facies model) of the temperature data for the three cases with different locations of the 4 temperature observations

Chapter 6

Two-facies 3-Dimensional SAGD reservoir model updating using EnKF

In the third case study we have utilized temperature records of observation wells along with production and injection well data to characterize and history match a 3-D two facies SAGD model. Similar to the previous two facies case study, the unknown parameter is the facies distribution that we aim to detect combining Discrete Cosine Transform (DCT) parameterization technique and the Ensemble Kalman filter (EnKF) algorithm. The benchmark case, which has continuous shale barriers, is generated using Sequential Indicator simulation (SIS) in Petrel. The 3-D reservoir model has 21 x 5 x 21 grid blocks with model dimensions of 250 meters x 750 meters x 35 meters. The observation data includes oil production rate (Q), Cumulative steam-oil ratio (cSOR) and temperature data from different sensor locations. The porosity is assumed to be constant 35% throughout the reservoir. The other reservoir properties are presented in Table (6.1)

Table 6.1: 3-D SAGD Model Reservoir Properties

Model Dimensions	21 x 5 x 21
Length in X,Y,Z direction	250 m x 750m x 35m

Porosity	35% constant
Permeability Range	Sand - 3000md; Shale - 50md
Formation Heat Capacity	7.4E2 KJ/m3/K
Rock thermal Conductivities	2.1E2 KJ/m/day/C
Temperature	18 C
No. Of wells	1 producer & 1 injector
Pressure	30 Bar
Facies Proportion (Benchmark Case)	60 % Sand 40 % Shale
Injected Fluid	Steam
Steam Quality	90%
Injection Temperature	285 C

Similar to the previous two facies case study, in this case also the 3-D SAGD model has shale and sand distributions with average permeability value. Facies distribution of the benchmark case is 60% Sand and 40% shale. Permeabilities of the sand and shale distribution were set to 3000 md and 50 md, respectively. The simulated dynamic data using the reference facies distribution in simulation is considered the true case and is assumed to be available at the end of every month.

6.1 Model Parameter Update

Similar to the previous two facies case study, the model parameter which was updated in the analysis step is facies distribution. The Kalman gain is computed through the covariance matrices at each analysis step of EnKF based history matching process and the SAGD model was tuned through the Kalman gain. Figure 6.1 and Figure 6.2 shows the reference facies distribution, initial mean facies distribution and updated mean facies distribution for layer 5 and layer 1 of the 3-D SAGD model.

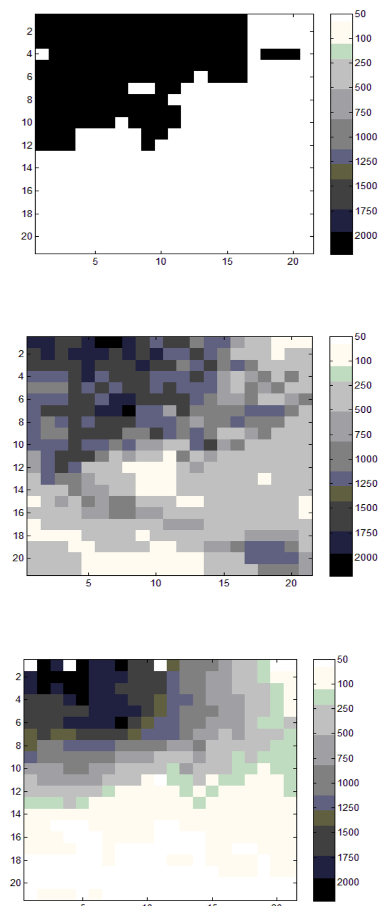


Figure 6.1: 3D-SAGD model facies distribution match of layer number 5
(a) Reference facies distribution
(b) Initial mean facies distribution
(c) Updated mean facies distribution

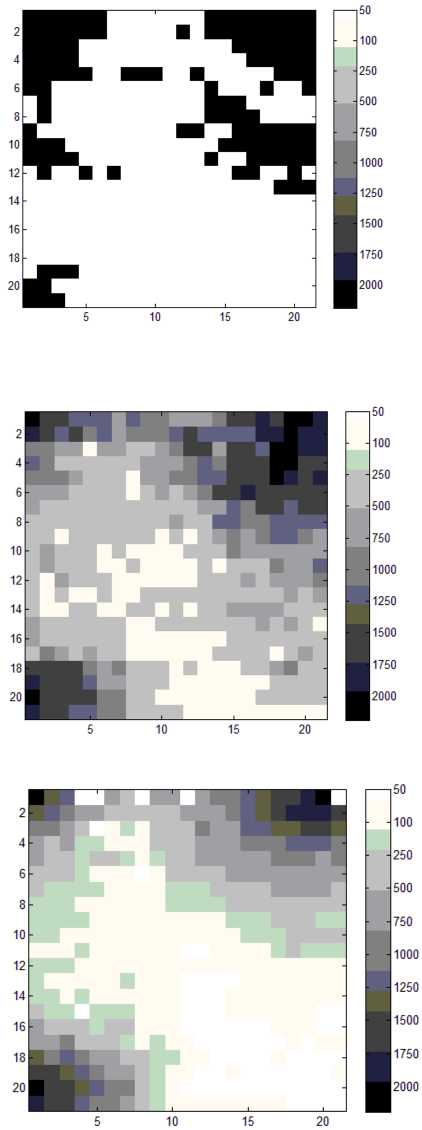


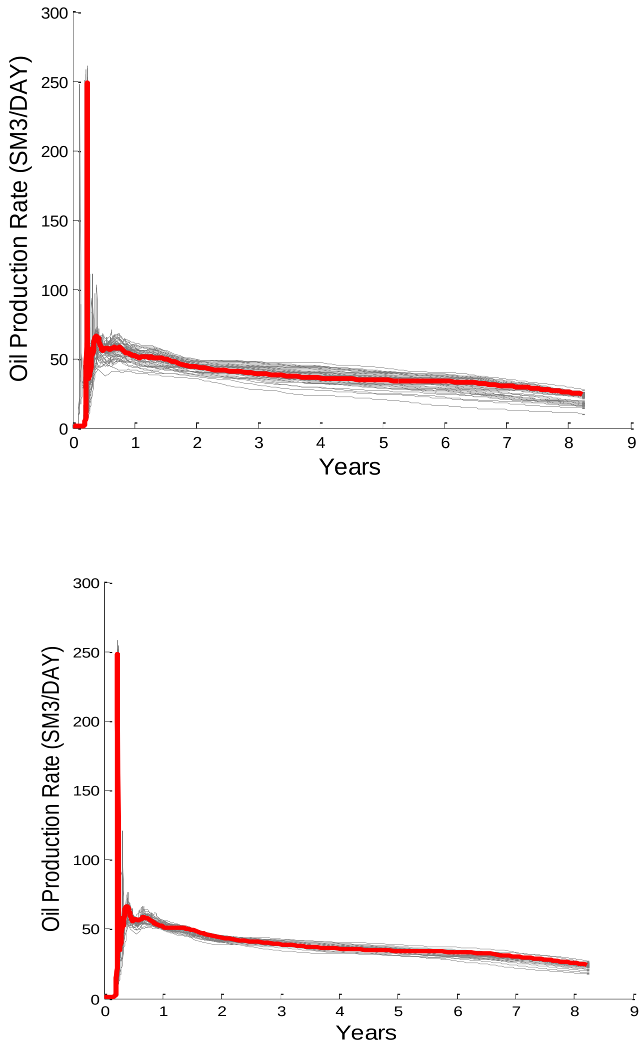
Figure 6.2: 3D-SAGD model facies distribution match of layer number 5
(a) Reference facies distribution
(b) Initial mean facies distribution
(c) Updated mean facies distribution

As shown in the above figures, after applying the DCT + EnKF to perform history matching, the updated mean facies distribution is close to the reference case. Thus the use of temperature data in conjunction with production data demonstrated significant improvement in facies detection and reduced uncertainty for SAGD reservoirs.

6.2 Dynamic Parameters Match

The oil production rate, steam oil ratio and temperature observations were assimilated in the history matching process and the updated parameters are plotted in the following figures. Using the reference facies distribution, an ensemble of 60 realizations were generated using sequential indicator simulation (SIS) method. These initial ensembles of facies distributions are updated at each data assimilation step. The history matching was performed for 21 update steps, assimilating the production data at the end of every three months. The after history match ensemble is generated by using the updated facies distribution in simulation. The redline curve represents the benchmark case or the true case whereas the grey lines represents the ensemble members prediction results. In each figure it can be clearly seen that the combination of EnKF and DCT is able to estimate the facies proportions that result in predictions matching the reservoir history closely, using the temperature observations in the data assimilation step.

Oil Production Rate

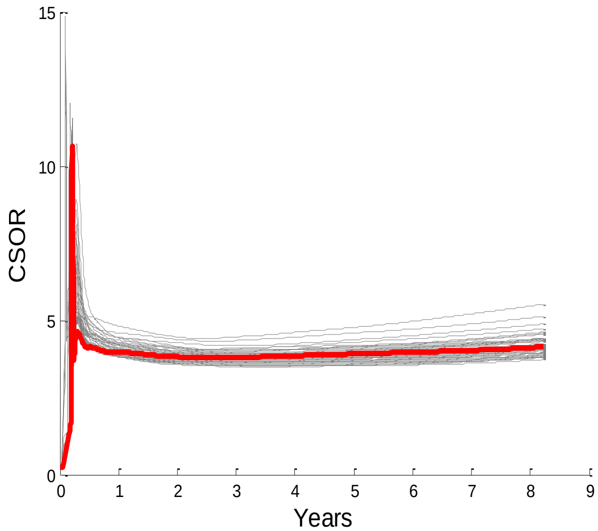


(a)Before History Match

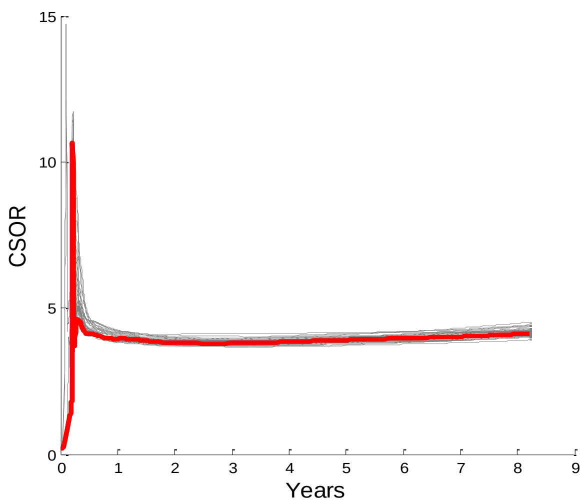
(b) After History Match

Figure 6.3: Oil Production rate(SM3/DAY) before and after history match for the 3D-SAGD model

Cumulative Steam-Oil Ratio



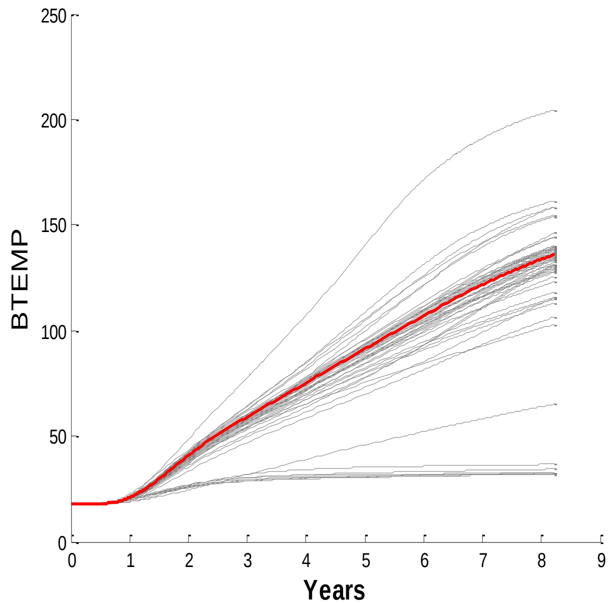
(a)Before History Match



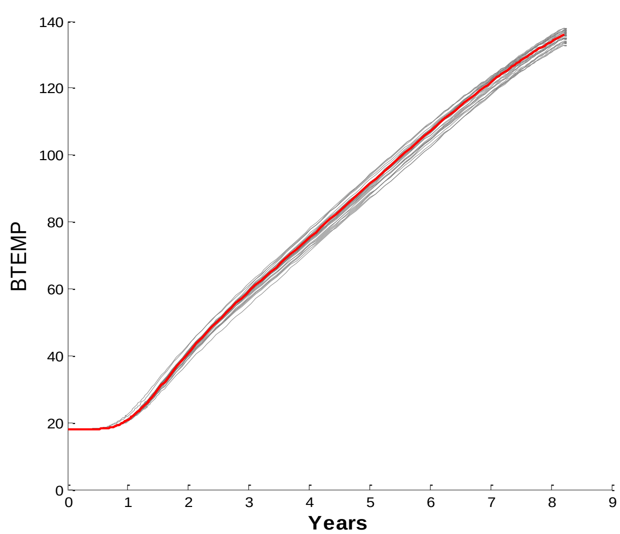
(b)After History Match

Figure 6.4: Cumulative Steam-Oil ratio before and after history match for the 3D-SAGD model

Block Temperature



(a)Before History Match



(b)After History Match

Figure 6.5: Block Temperature before and after history match for the 3D-SAGD model

Chapter 7

Realistic 3-Dimensional SAGD reservoir model updating using EnKF

In chapter 7 we have implemented EnKF to a realistic case study adapted from Surmont In-Situ Oil Sands Project. It's a 50/50 joint venture between ConocoPhillips and Total E&P Canada Ltd. operated by ConocoPhillips. Similar to the previous cases, the permeability static variables were constrained to available core data and temperature observations using the Sequential Gaussian Simulation (SGSIM) to estimate reservoir heterogeneity. The Surmont SAGD reservoir is located 65 km southeast of Fort McMurray which is located in northern Alberta, Canada. The Surmont SAGD nine well-pair pilot was used for EnKF based model updating study. In this case study the EnKF algorithm was prepared in the MATLAB programming software by interfacing it with the thermal reservoir simulator CMG-STARS and Petrel RE. The reservoir consists of high-porosity unconsolidated sand at a depth of around 400 m. The reservoir model has 56 x 59 x 74 grid blocks with nine pairs of injector and producer. Two heater wells are also used for preheating the reservoir prior to starting the production. The porosity is assumed to be a constant 0.35 value throughout the reservoir. The permeability ranges between 100 md to 21000 md.

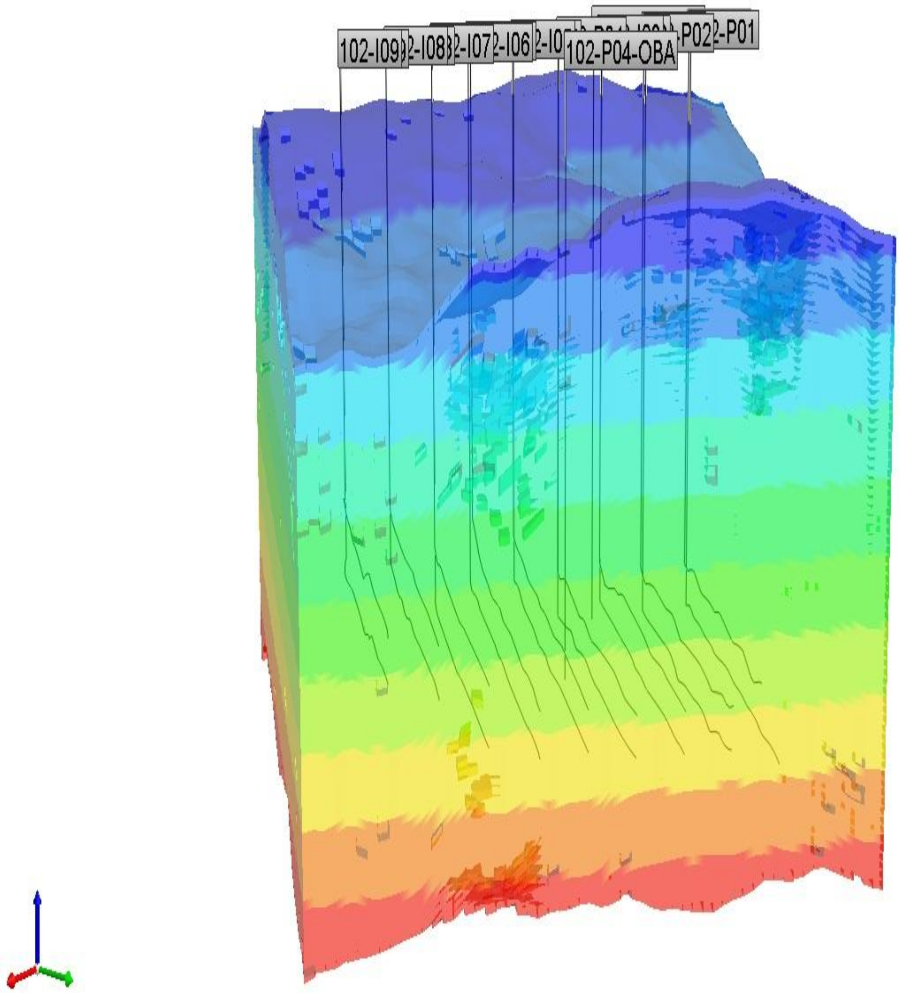


Figure 7.1: A cross section 3D view of the Surmont Model showing the location of wells

Table 7.1: Surmont Model Reservoir Properties

Model Dimensions	56 x 59 x 74
Length in X, Y, Z direction	800 m x 1000 m x 35 m
Porosity	0.35
Permeability Range	100 md to 21000 md
Initial Temperature	11 C
Pressure	1400kPa
API Gravity	8 deg
Viscosity	1e+6 cP
No. Of wells	9 pairs of injector & Producer
No. of Heater wells	2
Injected fluid	Steam
Steam Quality	90%
Injection Temperature	285 C

7.1 Updating the cumulative field production data along with the temperature observations

Using the reference permeability distribution, an ensemble of 50 permeability models (keeping high computational time in mind) is generated using SGSIM method with the same histogram and variogram as the reference field. Similar to the previous case study, the initial ensemble of permeability models is the input for the EnKF and is updated at the end of every 6 months till Oct. 2010 assimilating the most current injection, production and temperature data. The hard permeability data is assumed to be available at the well locations and the observations well locations. In Figure 7.2 to Figure 7.4 the initial ensemble of injection and production data is shown on the left and the updated ensemble is shown on the right. Similar to the previous case studies, the redline curve represents the true case and the grey lines represent the 50 realizations generated using the initial and updated permeability in simulation. In each figure it can be seen that the realizations of the ensemble move closer to the true values indicating reduction in uncertainty of Oil production rate, gas production rate and water injection rate. Thus improvements in the production and injection data predictions can be seen after history match. However no major improvements are seen in the permeability update (Figure 7.9 to 7.11) and even after the final update, the permeability update is under estimated.

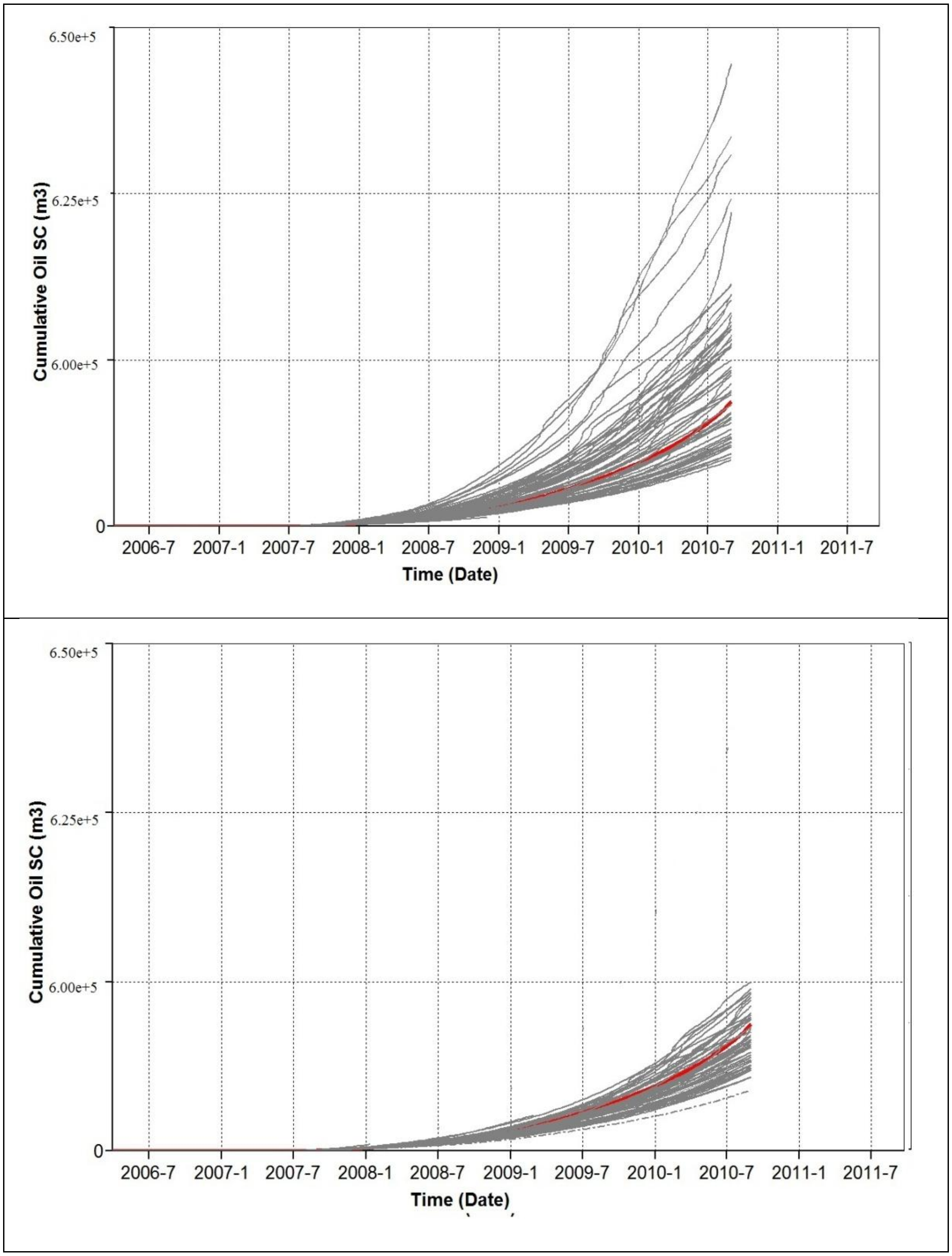


Figure 7.2: Cumulative Oil Production rate before and after history match

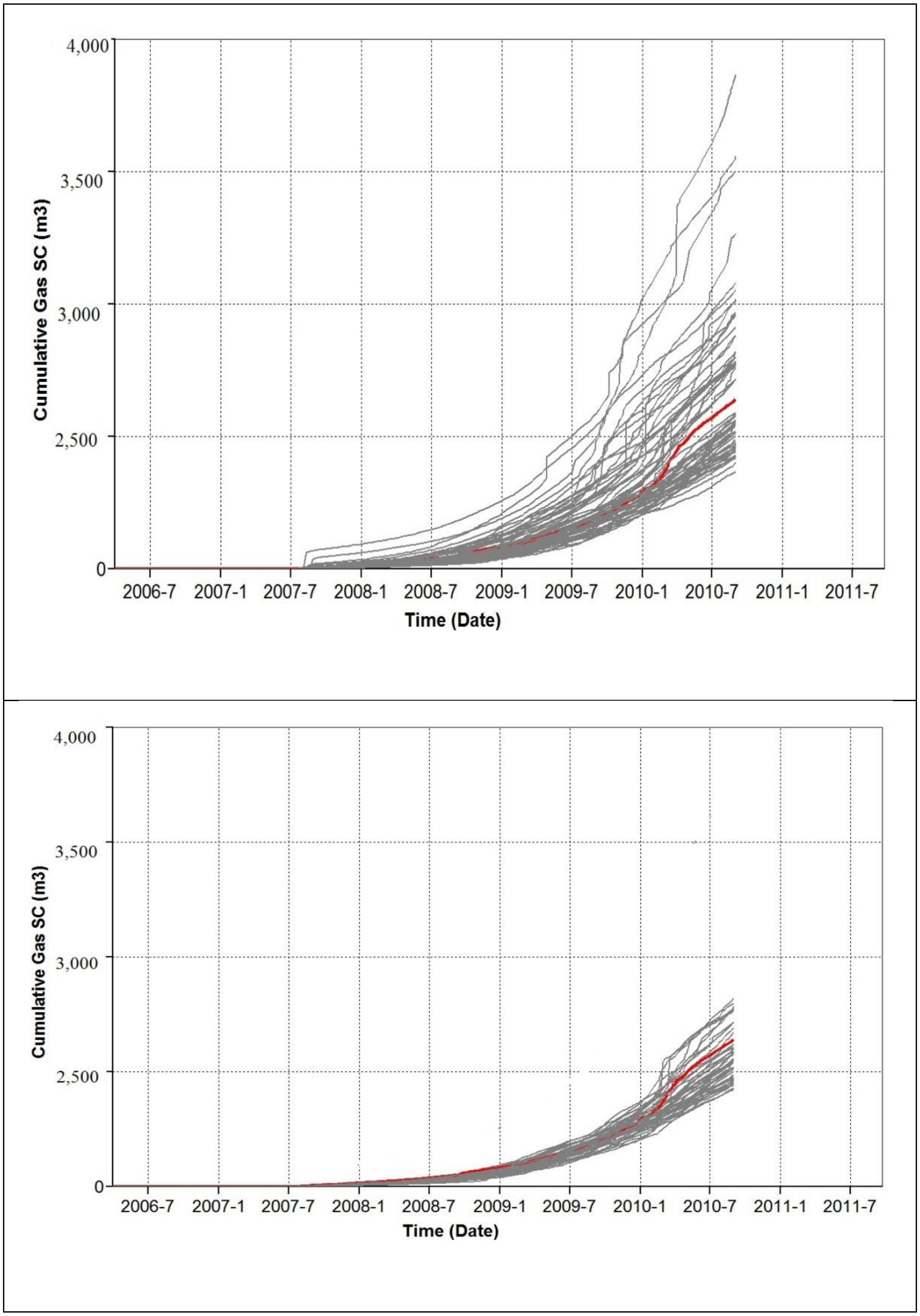


Figure 7.3: Cumulative Gas Production rate before and after history match

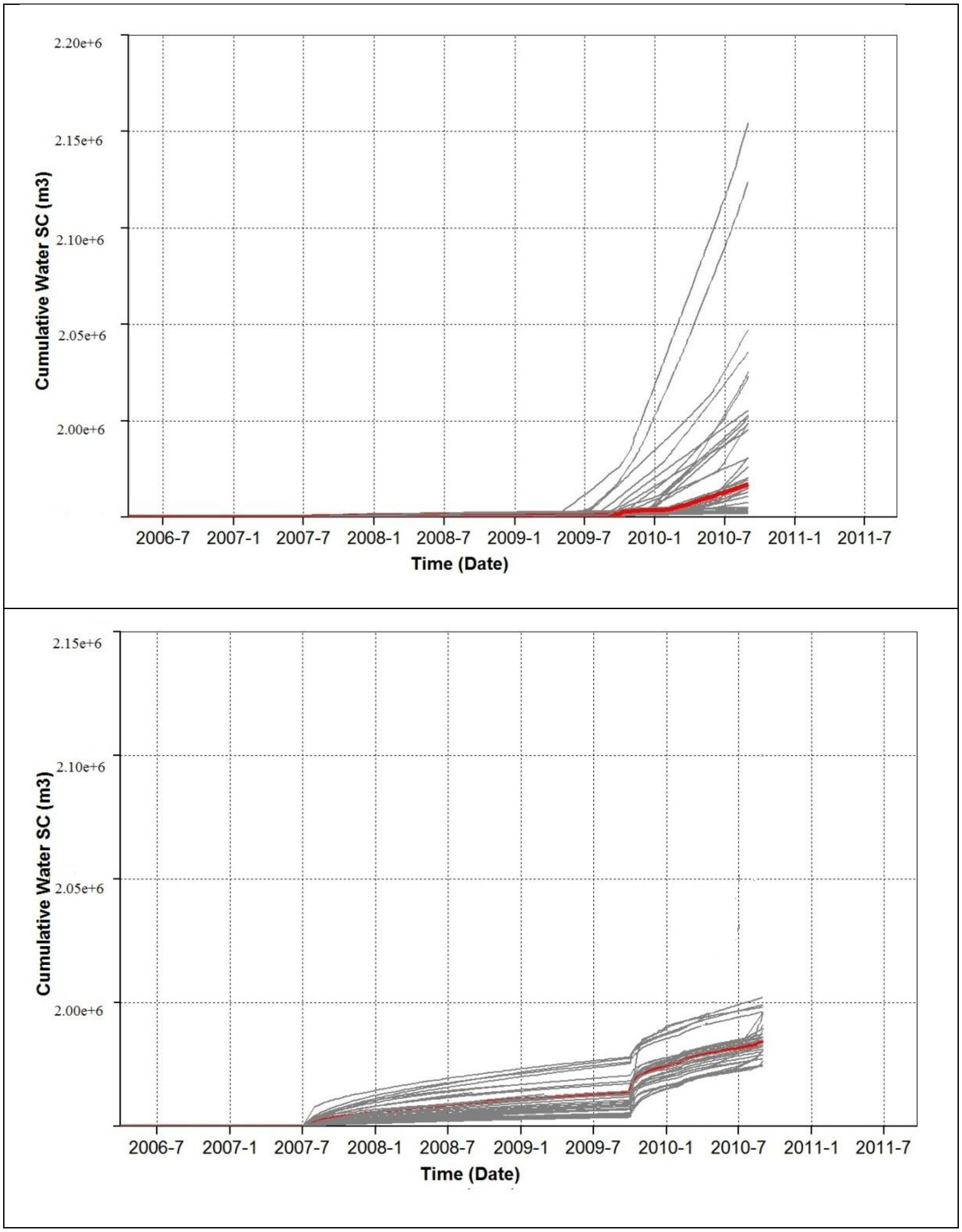


Figure 7.4: Cumulative Water Injection rate before and after history match

The growth of the steam chamber and associated drainage channels has the direct impact on oil rates and injection parameters during SAGD operations. To shorten the time required to reach the SAGD peak oil rates, the optimization of the injection parameters are necessary based on the different growth behaviors of the steam chamber. Multiple distributed temperature observations were placed along the horizontal well pairs to monitor the orientation of the steam chamber expansions (Figure 7.5) Red dot indicate the location of the DTS observation wells which are used to provide time and depth temperature observations for EnKF based reservoir model update). The choice of data type and observation locations are crucial for estimating model parameters and predicting state variables. Owing to the large size of the reservoir model, only one case study was carried out using the temperature data from four DTS well locations However if all the temperature observations (Figure 7.5) are used, improved model parameter estimation would be obtained. The number of realizations to be used in EnKF based reservoir model updating depends on the desired quality of estimates and the number of data integrated. Also for large reservoir models, large number of realizations would be required to avoid ensemble collapse and to obtain better estimates. However implementing all these data would be computationally expensive and would require faster system or parallel programming to reduce the computational time.

Figure 7.6 to 7.8 represents depth and time profile of the temperature data for the four observation wells used in the EnKF analysis step for model updating. Each temperature profile shows plateau features, which indicates a well established steam chamber around the observation well. In each figure, improvement in the updated temperature profile can be seen as compared to the initial profile clearly indicating that the use of temperature data in updating a SAGD reservoir enhances the understanding of reservoir heterogeneity. This clearly indicates that using more temperature observations during the data assimilation step would be useful in detecting potential steam barriers however while using more of the temperature data, both sampling cost and computational cost should be taken into account.

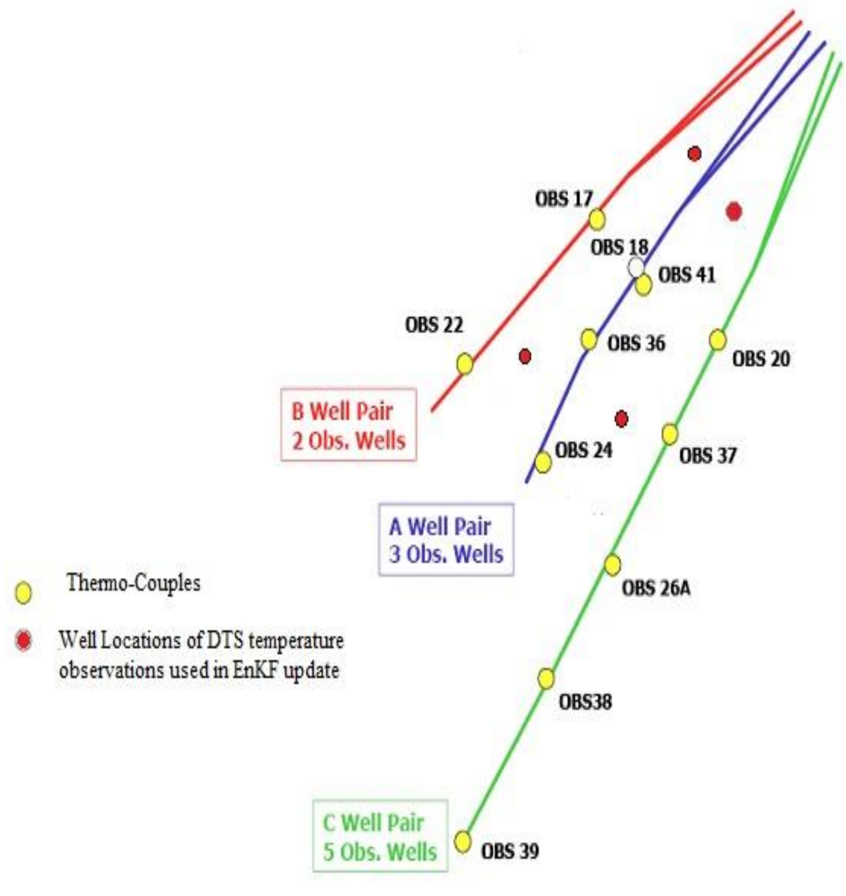


Figure 7.5: DTS well locations (ConocoPhillips Canada, "Surmont Pilot Performance: Resource Management Presentation to the EUB")

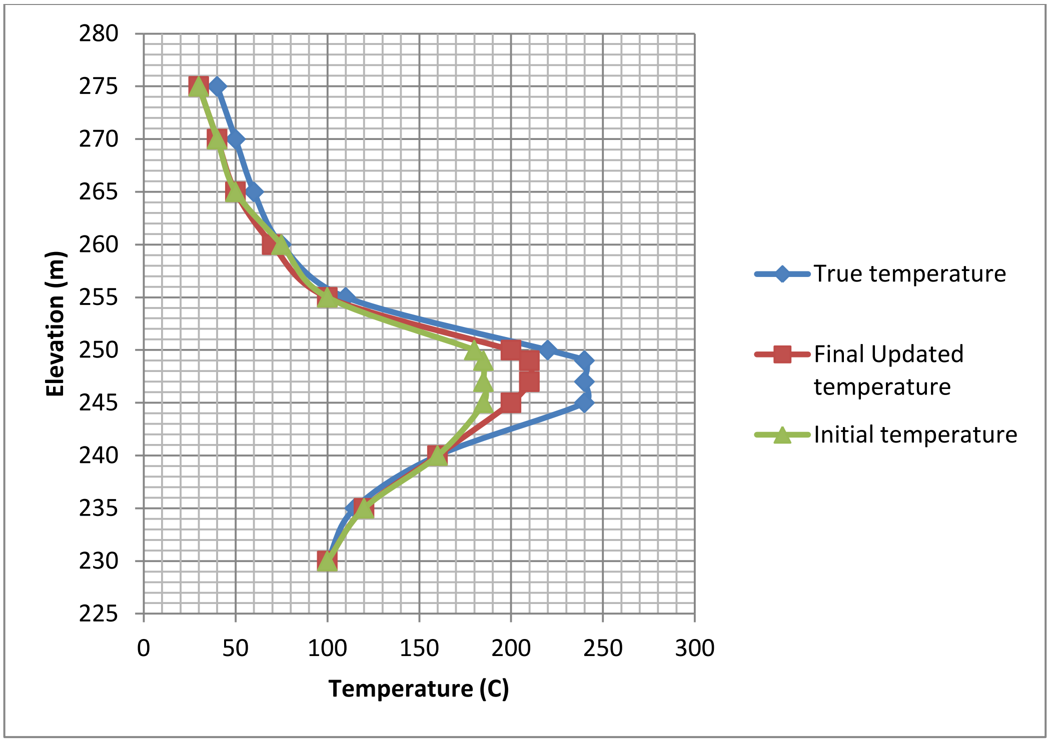


Figure 7.6: Temperature profile (Oct'10) of observation well 102-P04-OBA

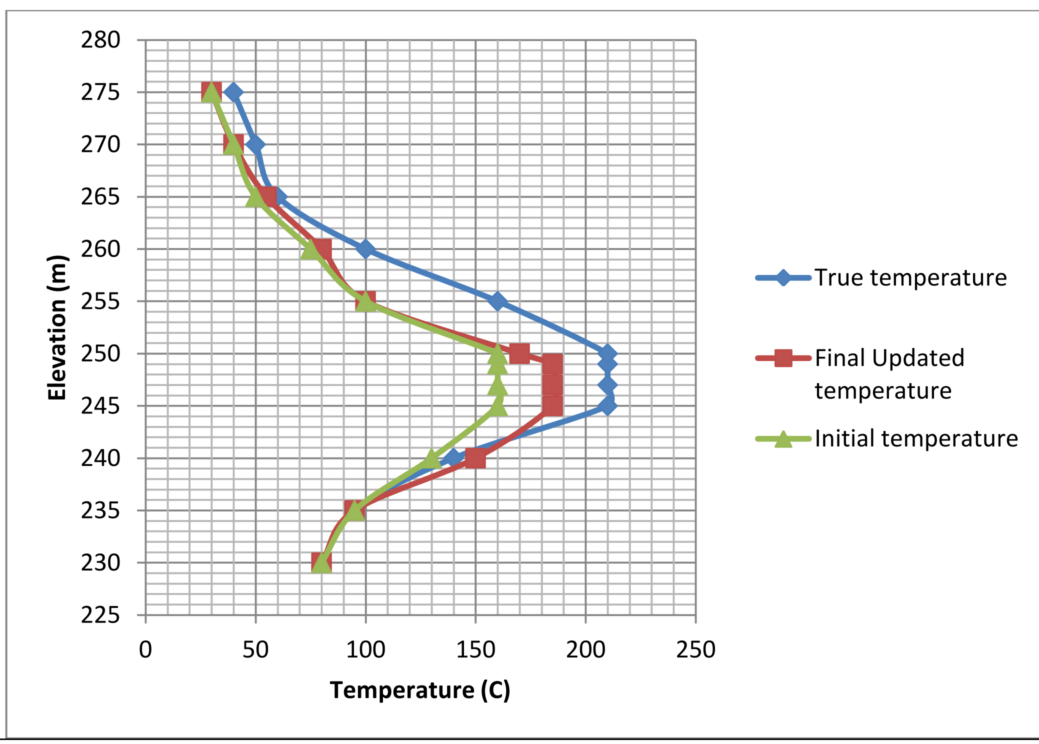


Figure 7.7: Temperature profile (Oct'10) of observation well 102-P03-OBA

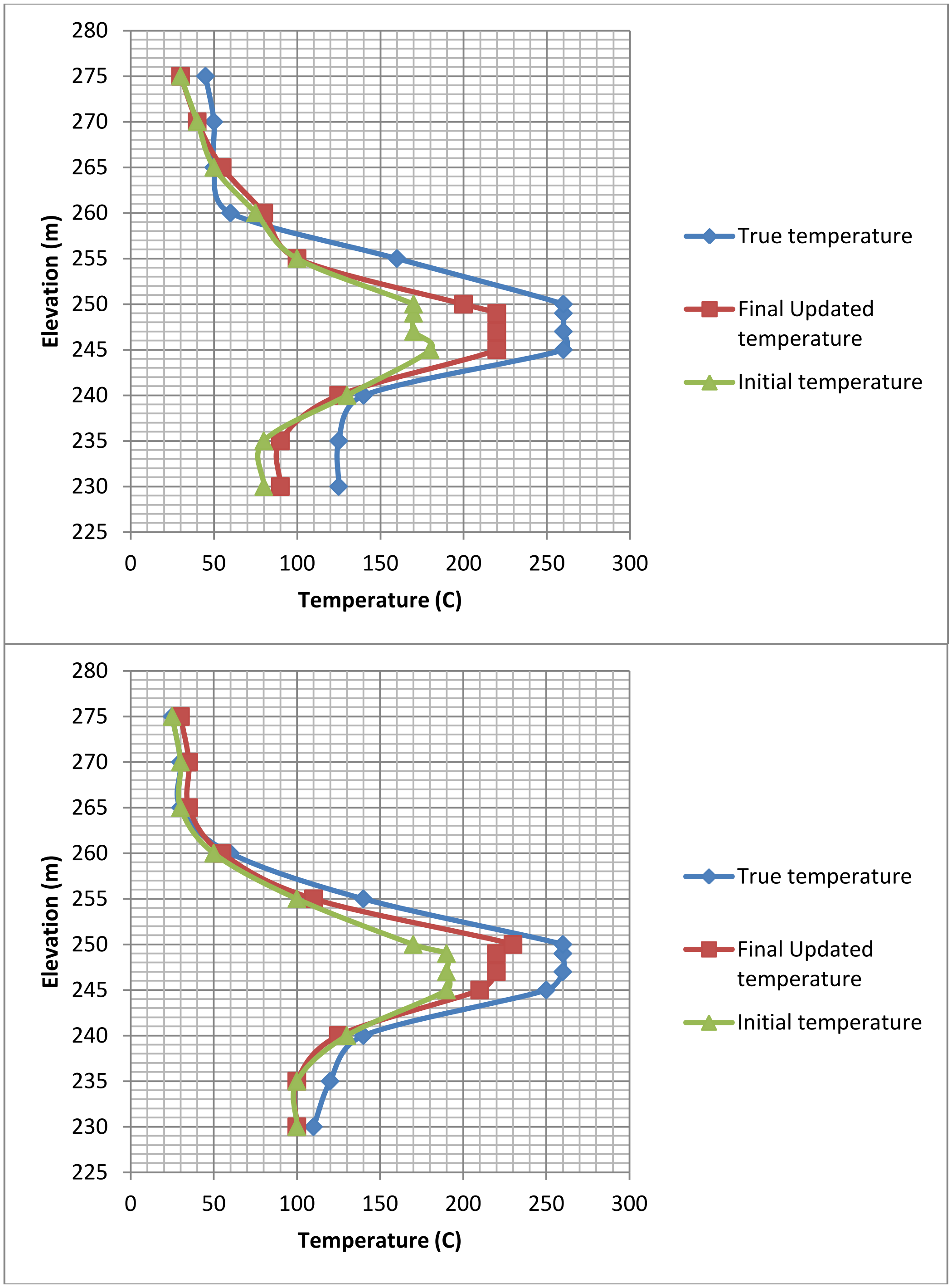


Figure 7.8: Temperature profile (Oct'10) of observation well (a) 102-P01-OBA (b) 102-P02-OBA

Initial Permeability field Updated Permeability field

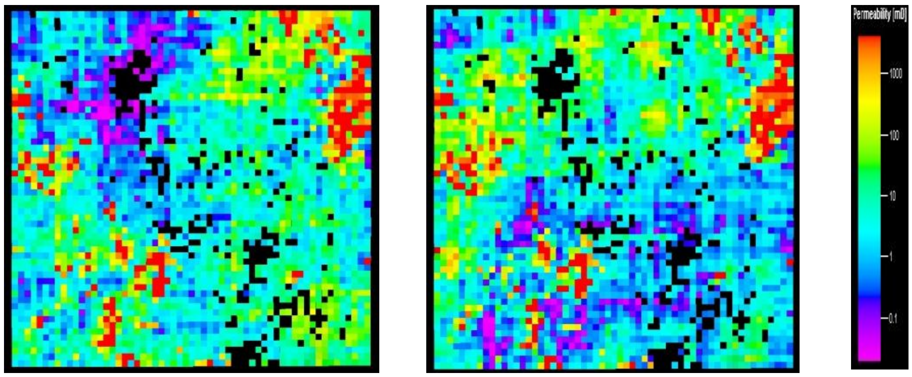


Figure 7.9: Permeability distribution match of layer number 40

Initial Permeability field Updated Permeability field

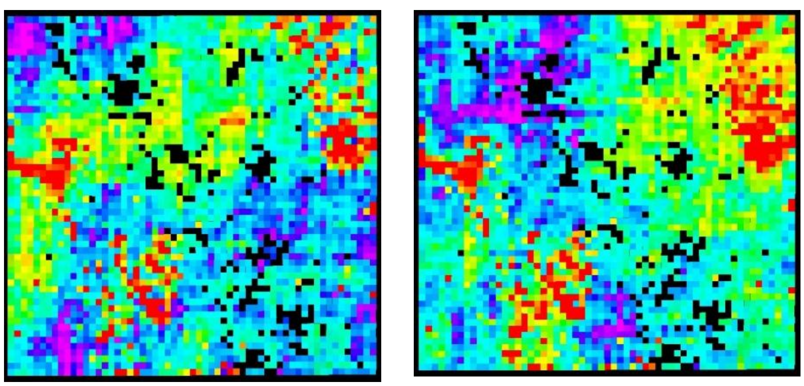


Figure 7.10: Permeability distribution match of layer number 44

Initial Permeability field Updated Permeability field

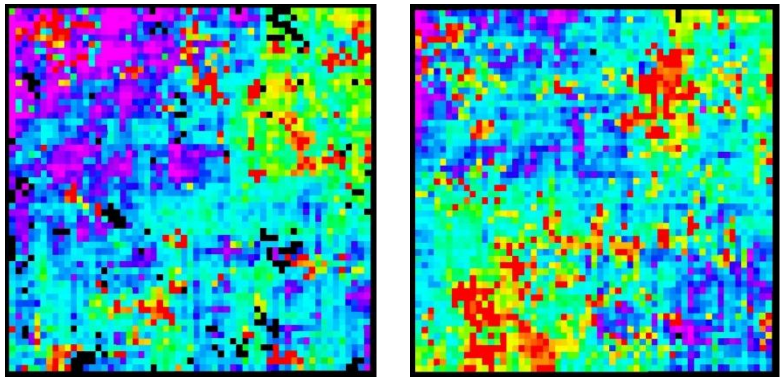


Figure 7.11: Permeability distribution match of layer number 48

7.2 Updating the cumulative production data of individual wells along with the temperature observations

In this case study we have updated the individual well cumulative production and injection data (cumulative oil production rate, cumulative gas production rate and cumulative water injection rate) in the data assimilation step along with the temperature observations to identify the importance that data from individual well holds in reservoir characterization and history matching. Similar to the previous case study the permeability distributions are tuned at the end of every 6 months till Oct. 2010 assimilating the most current injection, production and temperature data. Figure 7.12 to Figure 7.17 represents the initial ensemble and after history match ensemble of cumulative production rate for the individual well pairs. In each case the updated ensemble moved closer to the true case thus indicating improvements in the production data update and reduced uncertainty in data measurement. Though, similar to the previous case no major improvement is seen in the permeability match (Figure 7.18 to 7.20).

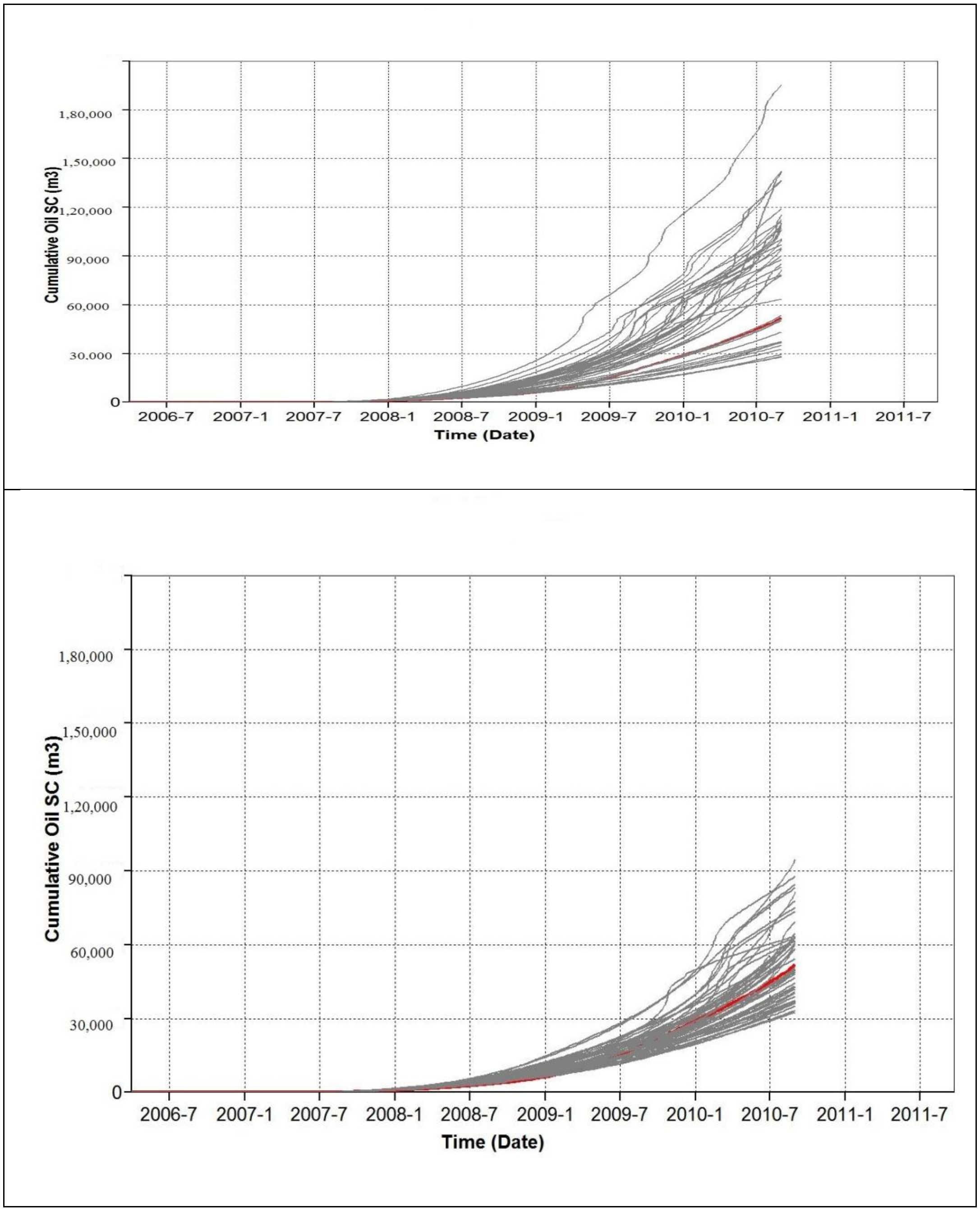
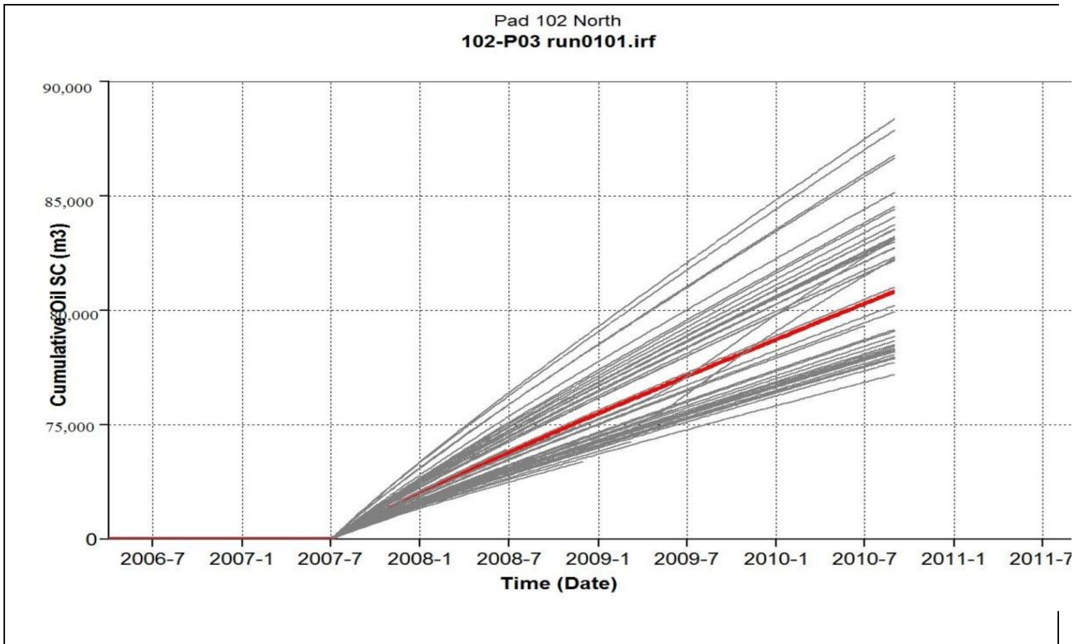


Figure 7.12: Cumulative Oil Production rate before and after history match for production well 102-P01



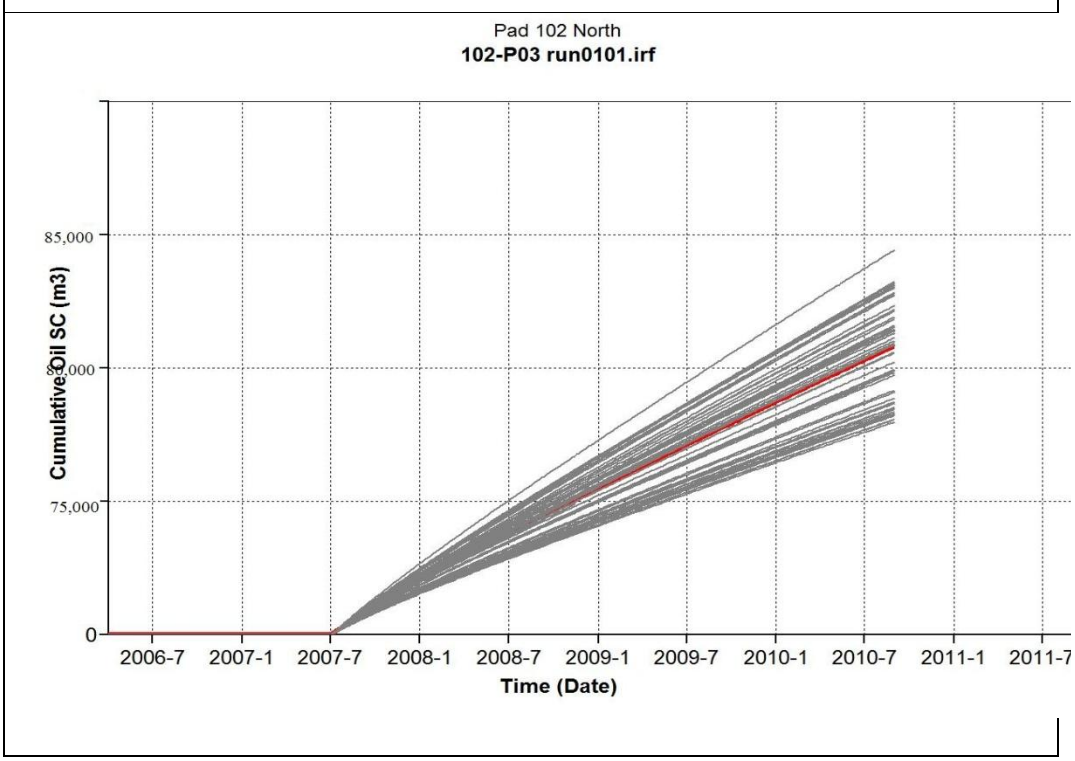


Figure 7.13: Cumulative Oil Production rate before and after history match for production well 102-P02

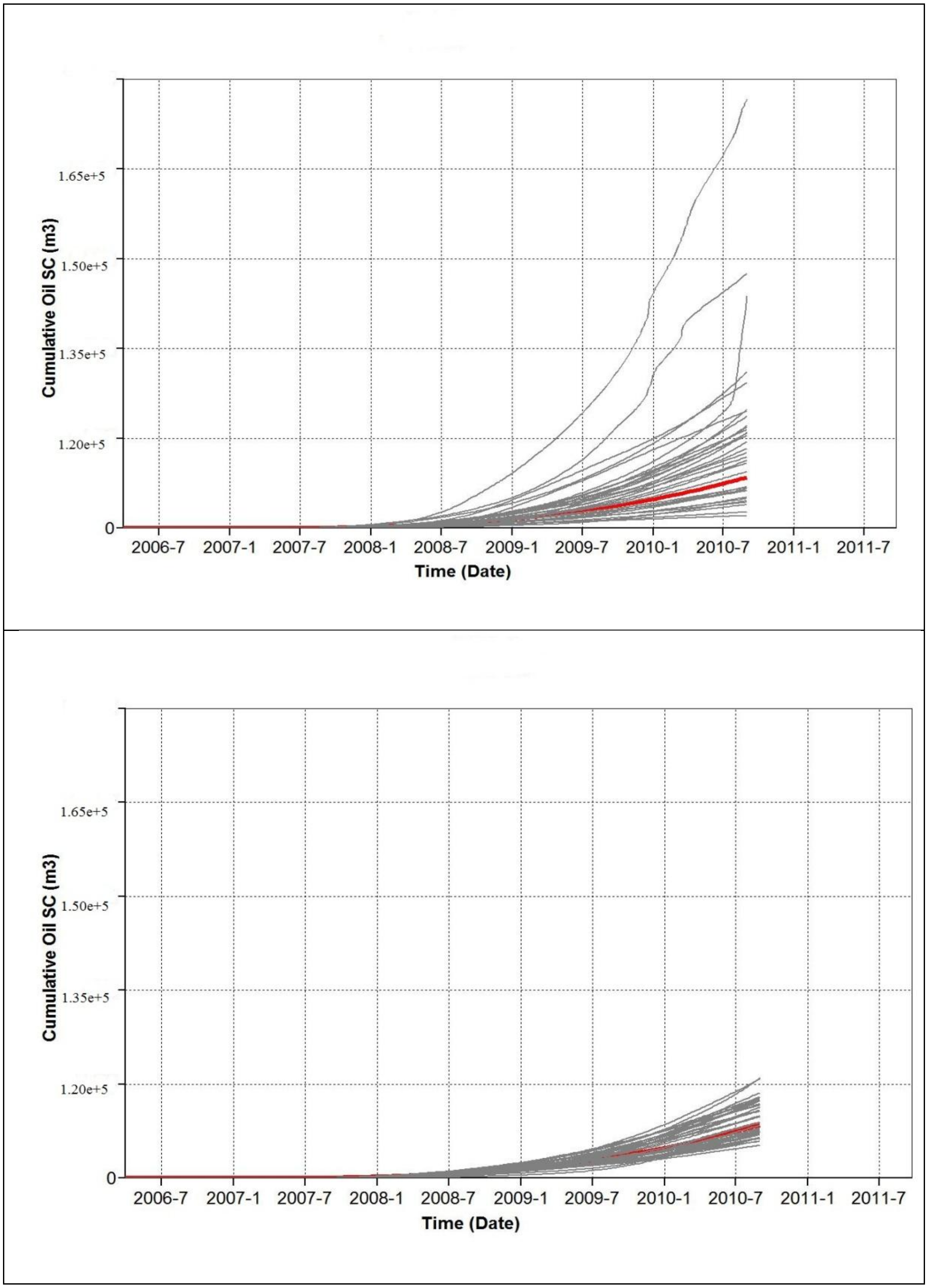


Figure 7.14: Cumulative Oil Production rate before and after history match for production well 102-P03

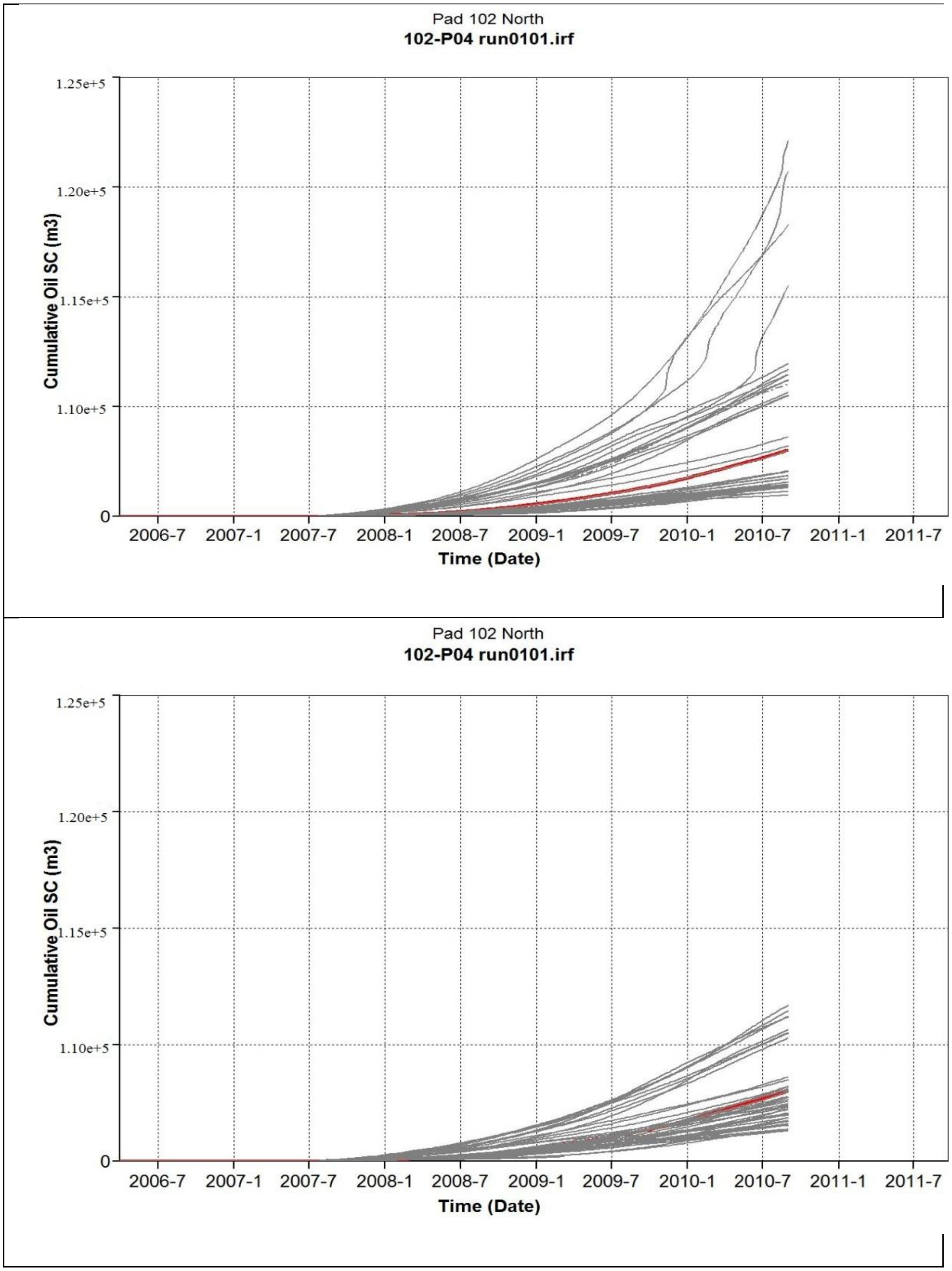
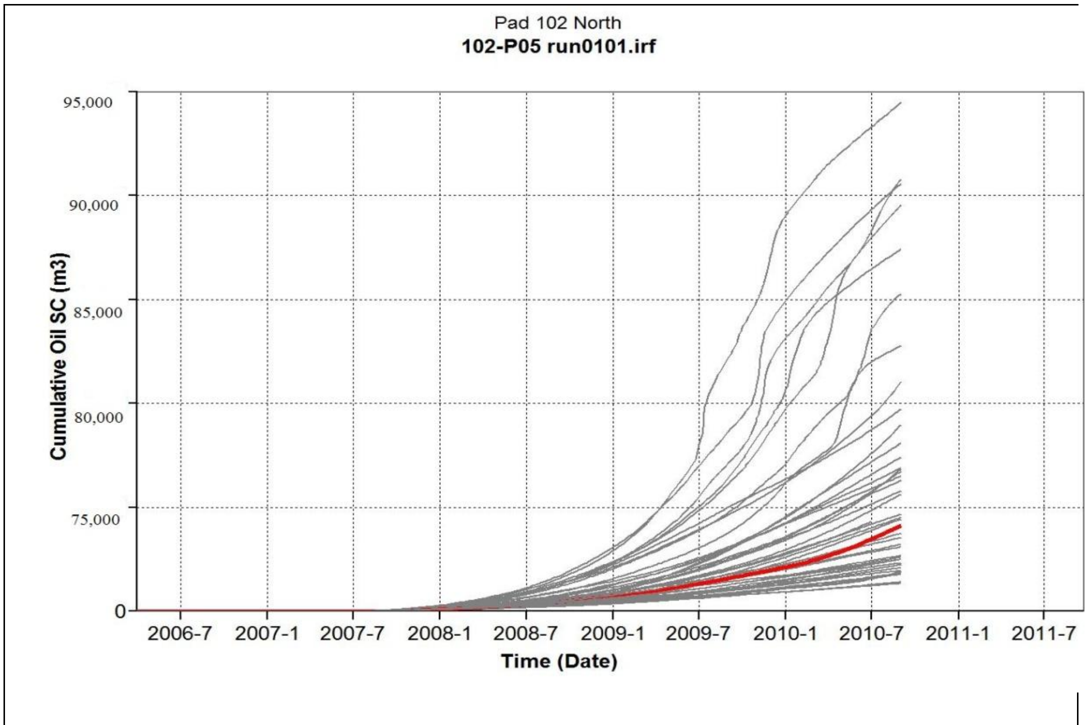


Figure 7.15: Cumulative Oil Production rate before and after history match for production well 102-P04



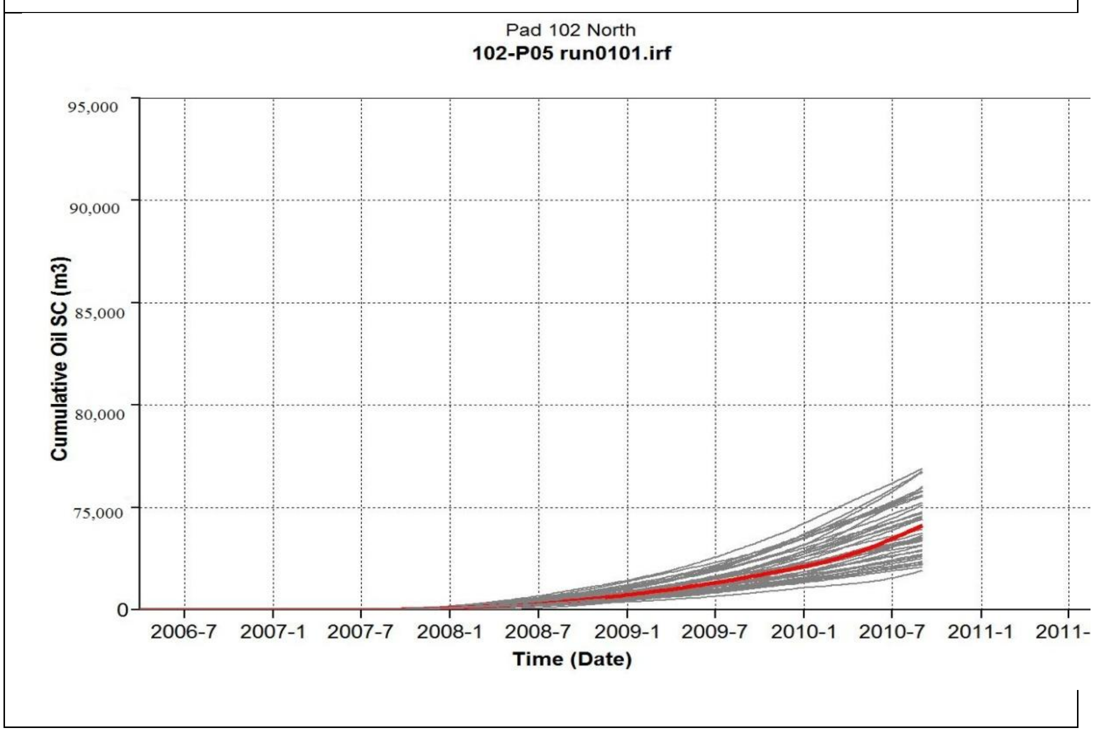


Figure 7.16: Cumulative Oil Production rate before and after history match for production well 102-P05

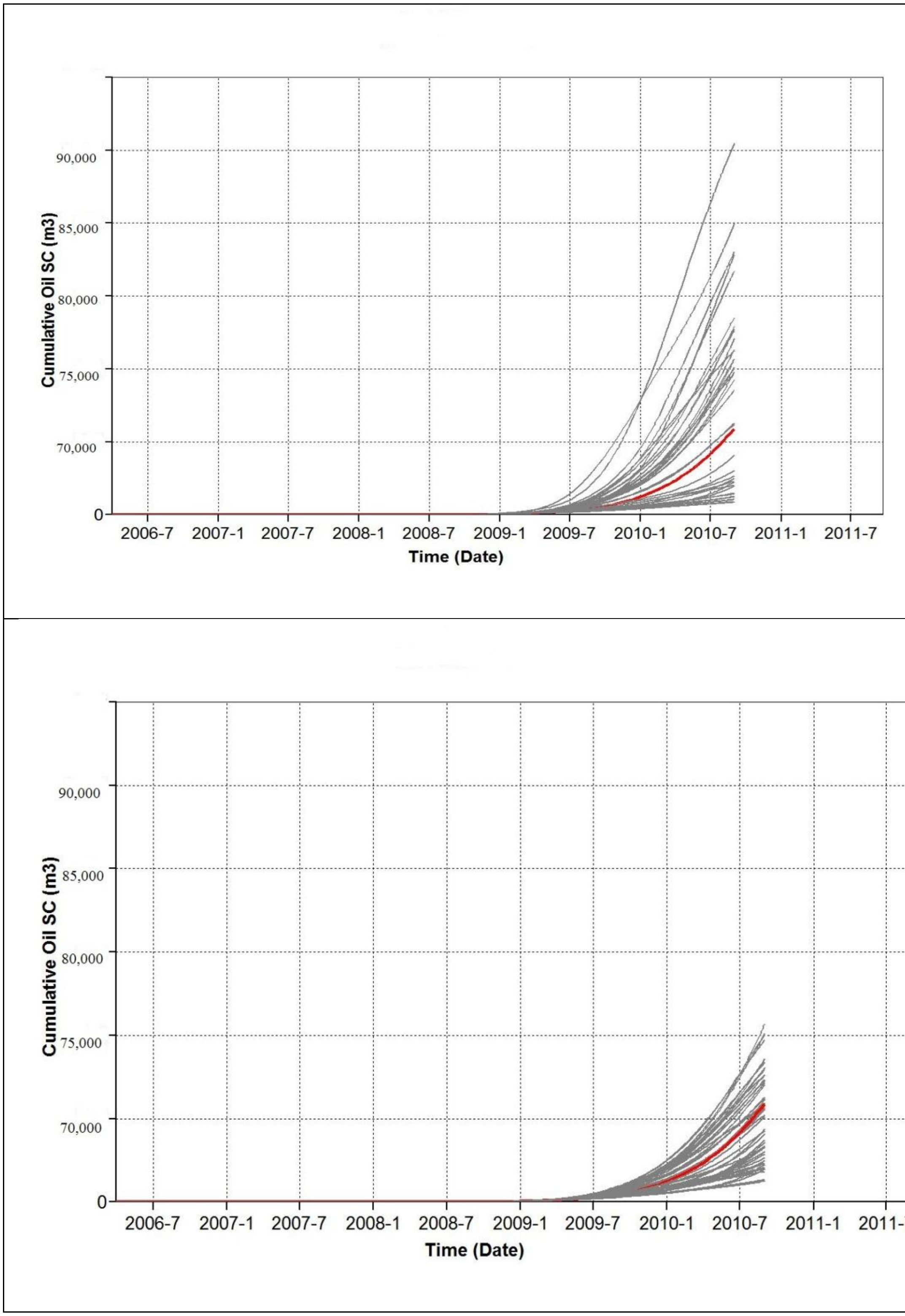


Figure 7.17: Cumulative Oil Production rate before and after history match for production well 102-P06

Initial Permeability field Updated Permeability field

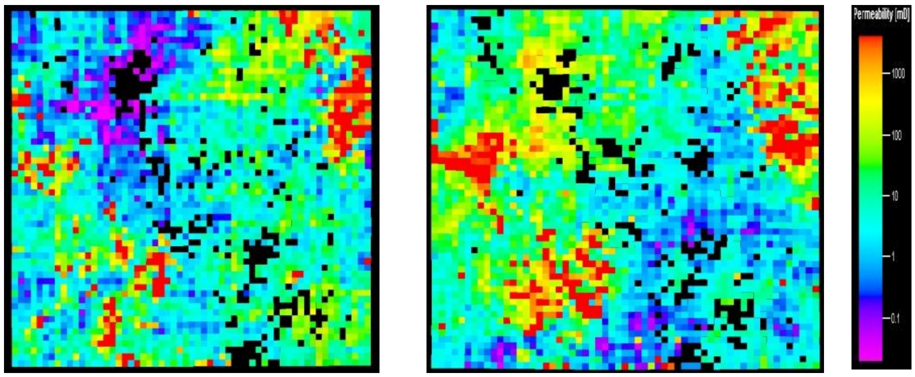


Figure 7.18: Permeability distribution match of layer number 40

Initial Permeability field Updated Permeability field

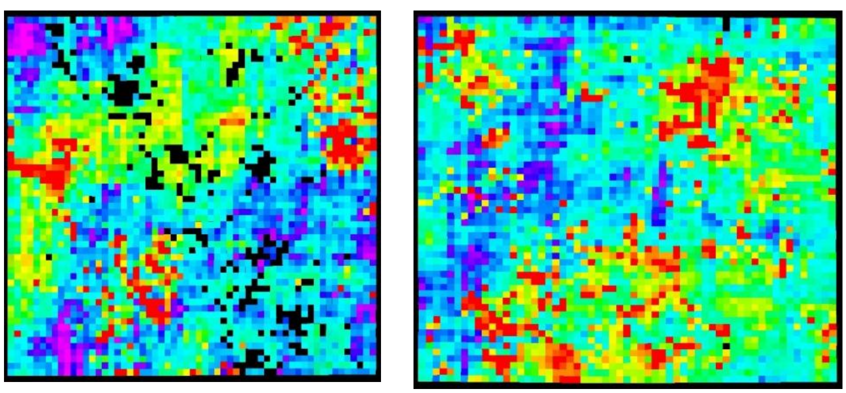


Figure 7.19: Permeability distribution match of layer number 44

Initial Permeability field Updated Permeability field

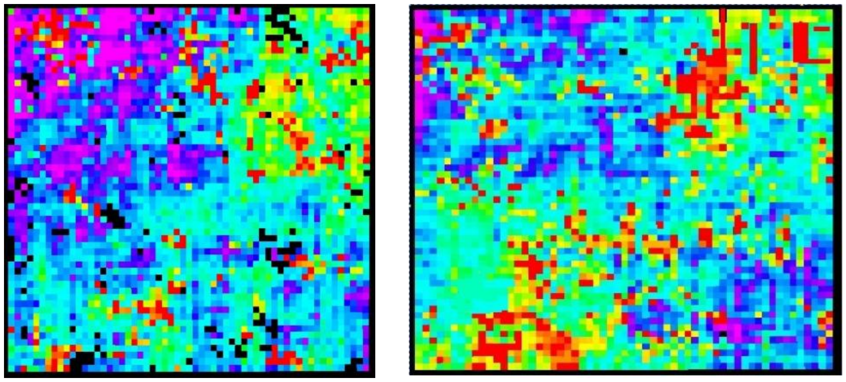


Figure 7.20: Permeability distribution match of layer number 48

Emerick et al, (2011) implemented covariance localization to history match a field case using the Ensemble Kalman Filter. He proposed that in a real field case having a large reservoir model, covariance localization is necessary to avoid the propagation of spurious correlations caused by sampling errors in EnKF. It also increases the degree of freedom available to assimilate data. The EnKF application with and without covariance localization is shown for a real case. The covariance localization showed a better match for permeability distributions and also better predictions as compared to the without localization case. Thus for history matching and characterizing the Surmont field case, the EnKF can be applied along with covariance localization. Also further studies is needed to find an optimal number of realizations and keep estimation accuracy unchanged or even improve it.

Chapter 8

Discussion, Conclusions & Future Work

8.1 Discussion

The ensemble Kalman filter (EnKF) approach for continuous model updating using production data along with temperature observations seems very promising approach for characterizing and history matching SAGD reservoirs. In this thesis we have presented an inverse modeling methodology based on the Ensemble Kalman filter by assimilating permeability measurements, production data and soft temperature observations for modeling and characterizing a SAGD operated petroleum reservoir model. The overall EnKF workflow is also modified for reservoirs whose petrophysical properties are not necessarily Gaussian by coupling it with the discrete cosine transform (DCT) algorithm for parameterizing the shale facies lables in SAGD reservoirs. The EnKF has been implemented on synthetic 2D and realistic 3D SAGD case studies and it has proved to be good for estimating model parameters (static parameters such as permeability) and predicting dynamic model's states (dynamic variables such as production rate, water injection rate, temperature observations). Also using EnKF, an ensemble of reservoir models assimilating the most current observations of production data and temperature observations are always available. Thus it also provides uncertainty assessment due to its ensemble nature. In the previous chapters we have presented the influence of assimilated temperature observations number and location on the quality of permeability and facies estimate for synthetic as well as realistic case study based on the Surmont SAGD thermal project. In order to investigate the effect of temperature observations on SAGD reservoir characterization, the number of DTS observations and their locations were varied for each study. The qualities of the history matched models were assessed by comparing permeability maps, facies maps, facies distribution and the Root Mean Square Error (RMSE) of the predicted data mismatch.

The case studies shown in this thesis and their conclusions can be summarized as follows:

- The first case study was implemented on a single facies 2D SAGD reservoir model containing high and low permeability regions which we aimed to detect using EnKF by assimilating production data and temperature observations. Three different cases with 0, 4 and 8 temperature observations (during data assimilation step) had been studied under this case study. Comparing the permeability maps for all the cases visually it was difficult to compare the quality of the updated permeability maps. Therefore Root mean square error (RMSE) graph of block temperature data were plotted for all the three cases to determine the quality of mismatched results. The RMSE of the predicted data was improved when DTS temperature observations were used. However, including more temperature observations than the optimum number showed no further improvement in results.

- The second case study was performed on a two facies 2D and 3D SAGD models having shale and sand facies whose permeability was assumed to be constant with an average value. In this case study we aimed to detect long continuous shale barriers whose detection is very important in SAGD reservoirs as they greatly affect their production performance (Butler et al, 1992; Chen et al, 2008).
- Similar to the previous case, three scenarios with 0, 4 and no temperature observations assimilation were presented in this case study. Comparing the updated facies maps it could be seen that when temperature observations were not used, even after many update steps the final model was unable to predict the shale barriers within the reservoir. However, when temperature observations were included, the facies match is close to the reference case and eventually led to improved shale barrier detection. Including more than optimum number of DTS temperature observations showed minimal improvement in history match as well as RMSE plot clearly suggesting the limiting (cut-off) need for DTS data.
- A sensitivity analysis is also carried out to analyze the effect of DTS locations for improved facies detection and reservoir characterization. For this analysis, four temperature observation assimilation had been used at different locations. Similar to the previous cases, the qualities of the history matched models were assessed by comparing facies maps and RMSE of the predicted data mismatch. The results indicated that the assimilation of DTS data from nearby steam chamber location has

significant potential in significant reduction of uncertainty in steam chamber propagation and production forecast.

The EnKF updated model parameters such as grid permeability values showed improvements by assimilating field observed data and simulation predictions such as oil production rate; cumulative steam-oil ratio and temperature observations. These improved model parameters update are crucial for SAGD field developments.

8.2 Conclusion

The ensemble Kalman filter (EnKF) had been implemented with Eclipse E300 and CMG STARS reservoir simulator to continuously update an ensemble of SAGD reservoir models assimilating real time data and observations. The discrete cosine transform (DCT) algorithm is coupled with EnKF for parameterizing the shale facies labels in SAGD reservoirs. The real-time temperature measurements from DTS in conjunction with the production data are assimilated successfully in two synthetic case studies, single facies and two facies model, for characterization, continuous shale barrier detection, and automatic history matching. Sensitivities of using different number of DTS observations and their locations were also investigated. The following conclusions can be drawn from this thesis:

- The EnKF is very efficient and robust method for real-time updating of reservoir models to confirm the newly collected production data. The total time for creating N*e* realizations of reservoir models to match the latest production data is about the cost of running N*e* reservoir simulations.

- EnKF's ensemble nature helps in uncertainty assessment of the reservoir model estimates. An ensemble of reservoir models that are consistent with the up-to-date production data are always available.
- In all the case studies there is significant update of the permeability and facies maps at the first few data assimilation step clearly indicating the importance of assimilating early production data for fast reservoir heterogeneity characterization. At later data assimilation steps, the averaged permeability and facies maps became closer and closer between different assimilation steps indicating that the production data at the later time carry less useful information on the reservoir heterogeneity as compared to ealy time data.
- The DTS temperature observations provided valuable information for reservoir characterization and shale barrier detection in SAGD reservoirs.
- The discrete cosine transform (DCT) along with EnKF is used to parameterize the facies labels. DCT-EnKF provided a highly attractive algorithm for updating and history matching petroleum reservoir models whose petrophysical properties are not necessarily Gaussian.
- For all the case studies temperature data assimilation showed evident improvement with DCT-EnKF history matched models in terms of;
    - Reduction in predicted data mismatch (RMSE)
    - Ability to preserve the reference distribution of model parameters

- Improved information about the SAGD steam chamber location, its movement and its rise rate within the reservoir.

- The temperature observations distributed uniformly within the steam chamber is ideal for better facies detection with reduced uncertainty.
- The assimilation of more temperature data is desirable; however, a few observations data could well serve the purpose of improved characterization.

8.3 Recommendations for future work

As for future work, the EnKF can be applied into the Surmont SAGD model using the temperature observations from all the distributed temperature sensors. Different type of transformation techniques such as Normal transform, Truncated Pluri-Gaussian, Gaussian mixture models can be applied to characterize non-Gaussian reservoir models. The localization of the covariance matrix may be studied to eliminate the effect of spurious data correlation caused due to large number of well pairs.

List of Abbreviations, Symbols and Nomenclature

y	=	State Vector
k	=	Time Indices
y_k^p	=	Prior State Vector
y_{k-1}^u	=	Updated State Vector
Ψ_{k-1}	=	State Transition Matrix
$C_{Y,k}^p$	=	Prior Covariance Matrix
w_{k-1}	=	Model Error
K_k	=	Kalman Gain Matrix
$C_{D,k}$	=	Data Error Covariance Matrix
F_k	=	Differentiable Equation
m_s	=	Static Parameters
m_d	=	Dynamic Parameters
d	=	Production Data
H	=	Matrix Operator
I	=	Identity Matrix
N_e	=	Number Of Realizations
Q	=	Oil Production Rate
cSOR	=	Cumulative Steam-Oil Ratio
T	=	Temperature Observations

2D	=	two-dimensional
3D	=	three-dimensional
CMG	=	Computer Modelling Group Ltd
COP	=	Cumulative Oil Production
EKF	=	Extended Kalman Filter
EnKF	=	Ensemble Kalman Filter
GSLib software	=	Geostatistical Software Library
KF	=	Kalman Filter
MATLAB software	=	Matrix Laboratory
MCS	=	Monte Carlo Simulation
MSD	=	Mean Standard Deviation
PVT	=	Pressure-Volume-Temperature
RMSE	=	Root Mean Squared Error
RSE	=	Root Squared Error
SAGD	=	Steam Assisted Gravity Drainage
SD	=	Standard Deviation
SGS	=	Sequential Gaussian Simulation
SIS	=	Sequential Indicator Simulation
STARS software	=	Steam, Thermal, and Advanced Processes

Reservoir Simulator

Superscript

1,2,3…	=	Ensemble Number
P	=	Predicted
j	=	Ensemble Member

a	=	Analyzed
T	=	Transpose

Subscript

k	=	Time Step
obs	=	Observed

Bibliography

Albahlani, A. M., and Babadagli, T. (2008). A critical review of the status of SAGD: Where are we and what is next?; Paper SPE 113283, presented at the SPE Western Regional and Pacific Section AAPG Joint Meeting, Bakersfield, CA. 31 March–2 April.

Anderson JL, Anderson SL (1999). A Monte Carlo implementation of the nonlinear filtering problem to produce ensemble assimilations and forecasts. Mon Weather Rev 127: 2741–2758.

Batocchio, M.A.P., Triques, A.L.C., Pinto, H.L.C.P., Lima, L.A.S., Souza, C.F.S . and Izetti, R.G., 2010. Case History- Steam Injection Monitoring with Optical-Fiber-Distributed Temperature Sensing. Paper SPE 127937 presented at the SPE Intelligent Energy Conference and Exhibition held in Ulrecht, Netherlands, 23-25 March.

Bertino, L., Evensen, G. and Wackernagel, H. (2003). Sequential data assimilation techniques in oceanography.International Statistical Review 71 (2), 223–241.

Chen, Q., Gerritsen, M.G. and Kovscek, A.R., 2008. Effect of Reservoir Heterogeneities on the Steam-Assisted Gravity-Drainage Process; SPE Reservoir Evaluation & Engineering, Vol. 11, No. 5, pp. 921 – 932, October.

Chen, Q., Gerritsen, M.G. and Kovscek, A.R., 2007.Effects of Reservoir Heterogeneities on the Steam-Assisted Gravity- Drainage Process. Paper SPE 109873 presented at the SPE Annual Technical Conference & Exhibition, Anaheim, California, 11-14 November.

Computer Modelling Group STARS Version 2009.10 User's Guide (2009). Computer Modelling Group, Calgary, Alberta, Canada.

Evensen G (1994a). Inverse Methods and data assimilation in nonlinear ocean models. Physica (D) 77: 108–129

Evensen G (1994b). Sequential data assimilation with a non-linear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. J Geophys Res 99(C5): 10 143–10 162.

Evensen G, van Leeuwen PJ (1996). Assimilation of Geosat altimeter data for the Agulhas Current using the Ensemble Kalman Filter with a quasi-geostrophic model. Mon Weather Rev 124: 85–96.

ECLIPSE 300 (STARS), *Reference manual and technical description.* Schlumberger GeoQuest, 2009.

Evensen G (1997). Advanced data assimilation for strongly nonlinear dynamics. Mon Weather Rev 125: 1342–1354.

Gu, Y. (2006). History Matching Production Data using the Ensemble Kalman Filter. *PhD Thesis*, University of Oklahoma, Norman, Oklahoma, 183

Gu, Y. and Oliver, D.S. (2005). History matching of the PUNQ-S3 reservoir model using the ensemble Kalman filter. *SPE Journal*, 10(2), 217 – 224

Gu, Y. and Oliver, D.S. (2006). The ensemble Kalman filter for continuous updating of reservoir simulation models. *Journal of Energy Resources Technology*, 128, 79 – 87

Houtekamer PL, Mitchell HL (1998). Data assimilation using an Ensemble Kalman Filter technique. Mon Weather Rev 126: 796–811

Houtekamer PL, Mitchell HL (1999). Reply. Mon Weather Rev 127: 1378–1379

Houtekamer PL, Mitchell HL (2001). A sequential ensemble Kalman filter for atmospheric data assimilation. Mon Weather Rev 129: 123–137.

Huseby, O., Valestrand, R., Nævdal, G. and Sagen, J. (2009). Natural and conventional tracers for improving reservoir models using the EnKF approach. *EUROPEC/EAGE Conference and Exhibition.* Amsterdam, The Netherlands.

Lorentzen, R. J., Berg, A.M., Nævdal, G. and Vefring, E.H. (2006). A New Approach for Dynamic Optimization of Waterflooding Problems. *Intelligent Energy Conference and Exhibition*, Amsterdam

Natvik LJ, Evensen G (2003a). Assimilation of ocean colour data into a biochemical model of the North Atlantic, part 1. Data assimilation experiments. J Marine Sys 40-41: 127–153.

Natvik LJ, Evensen G (2003b). Assimilation of ocean colour data into a biochemical model of the North Atlantic, part 2. Statistical analysis. J Marine Sys 40-41: 155–169.

Nævdal, G., Mannesth, T., and Vefring, E.H. 2002a. Instrumented Wells and Near-Well Reservoir Monitoring Through Ensemble Kalman Filter. Proc., 8th European Conference on the mathematics of Oil Recovery, Freiberg, Germany, 3-6 September.

Nævdal, G., Mannesth, T., and Vefring, E.H. 2002b. Near-Well Reservoir Monitoring Through Ensemble Kalman Filter. Paper SPE 75235 presented at the

SPE/DOE Improved Oil Recovery Symposium, Tulsa, 13-17 April. Doi: 10.2118/75235-MS.

McLennan, J.A. and Deutsch, C.V., 2006. Best Practice Reservoir Characterization for the Alberta Oil sands; presented in 7th Canadian International Petroleum Conference, Calgary, AB, Canada.

Queipo, N.V., Goicochea, J., Romero, D., Zambrano, A. and Bracho, A., 2002. Applications of Permanent Downhole Pressure, Temperature, and Flow Rate Measurements for Reservoir Description and Production Optimization: a Taxonomy, Processes, and Benefits. Paper SPE 77897 presented at the SPE Asia Pacific Oil & Gas Conference and Exhibition (APOGCE) held in melbourne, Australia, 8-10 October.

Reichle RH, McLaughlin DB, Entekhabi D (2002) Hydrologic data assimilation with the Ensemble Kalman Filter. Mon Weather Rev 130: 103–114

Redford, D.A., 1985. In Situ Recovery from the Alberta Oil Sands – Past Experience and Future Potential; Journal of Canadian Petroleum Technology, Vol. 24, No. 3, pp. 52 – 62, May - June.

Redford, D.A. and Luhning, R.W., 1999. In Situ Recovery from the Alberta Oil Sands – Past Experience and Future Potential Part II; Journal of Canadian Petroleum Technology, Vol. 38, No. 1 3, pp. 1 - 13.

Williams, L.L., Fong, W.S., and Kumar, M., 1998. Effects of Discontinuous Shales on Multizone Steamflood Performance in the Kearn River Field. Paper SPE 73174 presented at the SPE Annual Technical Conference & Exhibition, New Orleans, 27-30 September.

Wang, H., 2008.Application of Temperature Observation Wells during SAGD Operations in a medium Deep Burial Extra Heavy Oil Reservoir. Paper 2008-118 accepted for the proceedings of the Canadian International Petroleum Conference/ SPE Gas Technology Symposium Joint Conference, Calgary, Alberta, Canada, 17-19 June.

Yang, G. and Butler, R.M., 1992. Effects of Reservoir Heterogeneities on Heavy Oil Recovery by Steam- Assisted Gravity Drainage. Journal of Canadian Petroleum Technology, Volume 31, No. 8, pp. 37 - 4, October.

Zang. X. and P. Malanotte-Rizzoli (2003). A comparison of assimilation results from the Ensemble Kalman filter and the Reduced- Rank Extended Kalman filter. Nonlinear Processes in Geophysics, 10, 6, 477-6, 491.