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Seismic Assisted History Matching Using Binary Image Matching

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Abstract

This paper presents a history matching scheme that has been applied to production data and time lapse seismic data. The production data objective function is calculated using the conventional least squares method between the historical production data and simulation predictions, while the seismic objective function uses the Hamming distance between two binary images of the gas distribution (presence of gas (1) or absence of gas (0)) sequenced over the different acquisition times. The technique is applied to a UKCS (United Kingdom Continental Shelf) field that has deep-water tertiary turbidite sands and multiple stacked reservoirs defining some degree of compartmentalisation. Thirty five parameters are perturbed in this history match, they can be classified as volumetric parameters (net-to-gross, pore volume), transmissibility parameters (permeability, transmissibility), and end points of the relative permeability curves (critical saturation points). An initial ensemble of fluid flow simulation models is created where the full range of uncertain parameters are acknowledged using experimental design methods, and an evolutionary algorithm is used for optimization in the history matching process. It is found that permeability and critical gas saturation are key parameters for achieving a good history match, and that the volumetric parameters are not significant for this match in this particular reservoir. We also observe that matching only to production data marginally improves the seismic match, whilst matching to only seismic data improves the fit to production data. Combining both sets of data delivers an improvement for the production data and seismic data, as well as an overall reduction in the uncertainties. A unique feature of this technique is the use of the Hamming distance metric for seismic data history matching analysis, as this circumvents the use of the uncertain petroelastic model. This approach is easy to implement, and also helps achieve an effective global history match.

Introduction

The ability to predict the performance of an oil field in an efficient and timely manner is the desire of every reservoir engineer. This is coveted as it expedites efficient reservoir monitoring, management, planning and economic evaluation (Obidegwu et al., 2014). In order to achieve this target, different tools and techniques are employed to acquire, coordinate and interpret data obtained from the reservoir as input to the reservoir simulation model. This model has to confidently replicate the historical data for it to be considered worthy of realistic predictions, and this process of updating the reservoir model to satisfy the

historical data is known as history matching. Over the past years, production data (oil rates, water rates, gas rates, pressure) has been the main historical data available, however, four dimensional (4D) seismic data is now considered a major dynamic input for history matching. That a model is matched to production data is not a sufficient condition for it to make improved predictions (Sahni and Horne, 2006), the model needs to integrate all available data as well as the geologists interpretation of the reservoir in order to provide the most representative reservoir model or models (Landa, 1997, Landa and Horne, 1997, Wang and Kovscek, 2002). The need to monitor fluid displacement is a great challenge that has been successfully overcome with the use of 4D seismic technology (Hatchell et al., 2002, Lygren et al., 2002, Waggoner et al., 2002, Staples et al., 2002, Vasco et al., 2004, Portella and Emerick, 2005, Huang and Lin, 2006, Emerick et al., 2007, Kazemi et al., 2011), which is the process of repeating 3D seismic surveys over a producing reservoir in time-lapse mode (Avansi and Schiozer, 2011, Kretz et al., 2004). Quantitative use of 4D seismic data in history matching is an active research topic that has been explored extensively (Arenas et al., 2001, Aanonsen et al., 2003, Clifford et al., 2003, Gosselin et al., 2003, MacBeth et al., 2004, Staples et al., 2005, Stephen and MacBeth, 2006, Kazemi et al., 2011, Jin et al., 2012), the main challenge being quantitatively incorporating the 4D seismic into the reservoir model (Landa, 1997, Walker et al., 2006, Jin et al., 2011).

Figure 1 shows the different domains in which seismic data could be incorporated into the reservoir model as has been described previously (Stephen and MacBeth, 2006, Landa and Kumar, 2011, Alerini et al., 2014). The three main domains are: (1) The simulation model domain, where the observed seismic data is inverted to changes in pressure and saturation, and are then compared with the simulation output (Landrø, 2001); (2) The impedance domain, where the observed seismic data is inverted to changes in impedance, and the simulation model is forward modelled to derive impedances, and both impedances are then compared (Ayzenberg et al., 2013), or (3) The seismic domain, where the impedances derived from the simulation model are convolved with a wavelet to generate a synthetic seismic, and this is then compared with the observed seismic (Landa and Kumar, 2011). The aforementioned domains use seismic modelling, rock physics modelling or petro-elastic modelling to address this challenge, however these modelling processes are complex, time consuming, uses laboratory stress sensitivity coefficients, as well as Gassmann's equation assumptions (Landrø, 2001, Gosselin et al., 2003, Stephen et al., 2005, Floricich, 2006, Wen et al., 2006, Amini, 2014) . There have been other methods that circumvent the complex seismic modelling process (Landa and Horne, 1997, Kretz et al., 2004, Wen et al., 2006, Jin et al., 2012, Rukavishnikov and Kurelenkov, 2012, Le Ravalec et al., 2012, Tillier et al., 2013) which employed the use of image analysis tools, binary processing, or dynamic clusters to integrate the seismic data into the reservoir model. In this paper we propose a method where our seismic data and simulation data are converted to binary seismic gas maps and binary simulation gas maps respectively, such that we can compare the observed seismic data directly with the simulation output in the binary inversion domain (Figure 1). Our objective function for calculating the misfit of our production data will be the conventional least squares method, while our seismic objective function will be the Hamming distance method. The context of our study is set by a UKCS dataset which has six monitor surveys that have been shot at intervals of 12-24 months. The early years of the data will be history matched, while the later years will be used to validate the improved final models (Kretz et al., 2004, Landa et al., 2005).

Methodology

The concept of 4D seismic data integration is to complement production data. This is because 4D seismic data has high spatial and low temporal frequency while production data has low spatial and high temporal frequency (Jin et al., 2012). The corresponding characteristics of these data aid in obtaining realisitic models of the reservoir through a seismic assisted history matching scheme. History matching is considered an inverse problem (Kretz et al., 2004, Tillier et al., 2012), it is a process of simultaneously

perturbing reservoir parameters such that it can be represented as a minimization problem where observed dynamic data are used to condition reservoir models by reducing the misfit between the observed data and model predicted data through an objective function. The use of the conventional least squares formulation for computing production data objective function and misfit has been shown to be suitable and efficient (Oliver and Chen, 2011), such that it can be significantly reduced during the history matching process, and properly characterizes the error between the simulated data and the real data (Tillier et al., 2013); hence this approach is used in this work. However, applying the least squares formulation to compute the seismic objective function and mismatch has been shown to be unsuitable because of the nature of seismic data (Aanonsen et al., 2003, Roggero et al., 2012, Le Ravalec et al., 2012, Tillier et al., 2013), hence the need to search for a suitable alternative.

We propose an approach where observed 4D seismic data is converted to a binary seismic gas map by filtering out the low amplitudes (gas representations) and assigning them a value of one, while everything else is zero; and pore volume weighted gas saturation difference maps (monitor year minus baseline year) are also generated and then converted to binary simulation gas maps, whereby a value of one represents presence of gas, and a value of zero represents absence of gas. The generated binary maps are then compared using a seismic binary objective function. A definitive tool for matching binary images, pattern detection and pattern matching is the Hamming distance metric (Pele and Werman, 2008, Zhao et al., 2010, Bostanci, 2014). The Hamming distance (Hamming, 1950) is a metric measuring the distance between two binary objects by the number of mismatches among their pair of variables. Mathematically, it can be expressed as the sum of the absolute difference between two binary objects (Equation 1), where Bin(X) and Bin(Y) represent the binary models.

$$\text{Hamming Distance} = \sum \left| Bin(X) - Bin(Y) \right| \tag{1}$$

The Hamming distance is said to have an inherent robustness to noise, can be invariant to light changes and small deformations, has a high recognition rate of input patterns, and the algorithm is simple and easy to implement (Pele and Werman, 2008). The Hamming distance will be used as the seismic binary objective function to quantify the dissimilarity between the pore volume weighted gas saturation difference and the 4D seismic data difference. Some of the advantages of this approach are that it eliminates the magnitude of the difference in values of the simulator output and the seismic data (i.e. the gas saturation difference maximum range value is 100, while that of the 4D seismic difference amplitudes can be more than 10000), it bypasses the complex petro-elastic model procedure, and that it is fast and effective. The dexterity of the Hamming distance objective function is such that algorithms which are specifically designed for minimization of a function defined as a sum of least squares (Tillier et al., 2013) can also employ Hamming distance as an objective function, as squaring the Hamming distance values i.e. ones and zeros, leaves them unchanged. The selection of appropriate weight coefficient values is usually driven by reservoir engineering experience and can be case dependent (Tillier et al., 2012). For the production data, the practice of boosting the effects of the ill-fitted production data was adopted, and this is done by selecting the weights as being proportional to the square of the difference between the data computed for the base case model and the observed data (Kretz et al., 2004); while the binary seismic data are equally weighted. The combined production data and 4D seismic data objective function is normalized (Kretz et al., 2004) such that at the beginning of the history match, the combined misfit is a value of one. In order to convert the gas saturation from the simulation model and the 4D seismic data to binary maps, cut-off values representing thresholds need to be obtained. These can be derived from a calibration exercise using seismic forward modelling, or by interactive interpretation which requires a clear understanding of the 4D seismic response in terms of the dynamic behaviour of the reservoir (Jin et al., 2012). A combination of both methods is utilised in this work, where seismic forward modelling is used to determine the initial threshold values. Then, integration of reservoir engineering knowledge,

injector and producer well activities, reservoir geology and structural contour, as well as 4D seismic concepts are then applied to generate the seismic binary maps.

Below are some tips on interpreting a suitable seismic threshold:

a. The reservoir pressure should be below bubble point pressure, or at least should have previously been below bubble point pressure, so that there will be gas (exsolved gas) present in the reservoir.
b. The presence of gas signal around a producer well is validated from gas production profile of the well.
c. The gas may be present at expected locations, for example at local structural highs.
d. As we are aware that amplitude decrease (softening) is a consequence of gas, as well as pressure increase (Calvert et al., 2014), the amplitude decrease caused by an increase in pressure around a water injection well is removed from the analysis; however in the case of a gas injector well (where an increase in pressure and the presence of gas cause the same softening effect on seismic), the magnitude of the pressure and gas saturation will need to be determined in order to ascertain which has a more dominant effect on the seismic.

To perform the history match, an initial ensemble of models is created using the Latin Hypercube Experimental Design (LHED) method (Roggero et al., 2007), as multiple models have extensive coverage of the search space and deliver robust results. The initial input parameter sampling is important, and is usually carried out using experimental design methods, such as Plackett-Burman, LHED or Factorial Design (Schulze-Riegert and Ghedan, 2007, Zubarev, 2009). The LHED is a statistical method for generating a sample of plausible collections of parameter values from a multidimensional distribution, and it is useful for exploring the uncertainty range (Schulze-Riegert and Ghedan, 2007). Evolution strategy algorithm is used for the optimization process to calibrate the uncertain values in the reservoir. The evolutionary algorithm is based on the notion of Darwinian evolution, it deals with concepts such as selection, recombination and mutation, and it is often used for reservoir history matching (Bäck, 1996, Soleng, 1999, Romero et al., 2000, Williams et al., 2004, Schulze-Riegert and Ghedan, 2007). In history matching, the termination criteria is usually until the objective function is small enough, convergence is obtained, or the number of iterations exceeds a maximum value (Tillier et al., 2012). The termination criteria used in this work is the convergence criteria. When convergence of the objective function is achieved, an improved set of models and their accompanying uncertainty is generated. One of the advantages of using this approach is that we can update multiple initial realizations to match the same dynamic data to assess uncertainty reduction in the reservoir characterization due to the integration of dynamic data, and this is similar to the randomized maximum likelihood method (Liu et al., 2001, Wen et al., 2006).

Application

So far we have introduced a method of seismic assisted history matching using production data and binary maps of gas saturation. We now apply this concept to field data, with the aim of history matching the observed data, as well as forecasting the future production profiles and gas saturation distribution as a means of validating our new improved models. This history matching technique will be applied using production data only, seismic data only, and a combination of production data and seismic data. The seismic assisted history matching workflow is shown in Figure 2.

The dataset is from a UKCS turbidite field (Martin and Macdonald, 2010). In this field, the reservoir fluid is black oil with an API gravity ranging from 22° to 28° at a temperature of 120^oF (48.89^oC). Initial

reservoir pressure is approximately 2900 psi (19.99 MPa) (at depth 1940m TVDSS) whilst bubble point is 2850 psi (16.65 MPa) at the top reservoir level, and the solution gas-oil ratio (GOR) is 354 scf/bbl (62.99 sm^3/m^3) (Falahat et al., 2014). In this particular field, there is known to be gas exsolution, gas mobilisation, and then re-pressurisation with subsequent dissolution. During the course of production, poor connectivity led to lack of support from injectors. This combines with a weak aquifer influx to give a strong pressure decrease in some areas, and a drop below bubble point with the consequent liberation of free gas. The drilling plan adjusted for this phenomenon and recovered the pressure (Govan et al., 2006).

There are multiple vintages of seismic shot across this field for reservoir management purposes, and for our current work the preproduction baseline in 1996 and six monitors shot in 1999, 2000, 2002, 2004, 2006 and 2008 are selected. These data have been cross-equalised by the operator for 4D seismic interpretation purposes, and have a non-repeatability NRMS noise metric (Kragh and Christie, 2001) of approximately 31% (Falahat et al., 2014). The data have been transformed into relative impedance traces by coloured inversion (Lancaster and Whitcombe, 2000). An isolated sector is identified for study that is segmented by two major EW trending normal faults. The reservoirs consist of multiple stacked, interconnected and amalgamated discrete sand bodies. The sediment system is thus expected to be highly compartmentalised, with both vertical and lateral connectivity being a major reservoir management issue. The T31 producing interval is mapped for the purpose of our study as it is the main reservoir in which gas exsolution occurs. This particular reservoir interval has a variable character ranging from thin inter-bedded sands and shale to massive sands. The T31 is divided into two units, T31a and T31b, separated by a thin shale. There are sheet-like units in this sector typically of 10m to 20m thick that can be mapped on the seismic over a large proportion of the area (Martin and Macdonald, 2010). The ‘sum of negatives’ attribute is employed for our 4D seismic analysis, this attribute sums all negative amplitudes over the T31 reservoir interval defined between the top T31a and base T31b. This is used as it has been demonstrated in past work to be sensitive to the reservoir conditions when the sands are known to be softer than the shales - giving a high to low seismic impedance contrast and a negative relative impedance (Jack et al. 2010). Figure 3 shows an outline of the reservoir, the position of the injectors and producers, and the timeline of activity of the wells relative to the multiple seismic data surveys. There are 10 years of production activity, it should be noted that the history matching will be implemented for the first 5 years, while the remaining 5 years will be used to validate our history matching process and forecasting ability.

Over the years of production, it has been observed that the major challenges to the field development and management plan are the field connectivity and the representation of its numerous geobodies. These geobodies were derived from the 3D seismic interpretation and used for geological model construction. A sensitivity study was carried out to determine which geobodies were most significant to our seismic assisted history matching objective function and this is shown in Figure 4. Combining the geobody regions and global parameters, we were able to identify 35 parameters, which include the permeability, porosity, net-to-gross, pore volume, geobody transmissibility, connate water saturation and critical gas saturation to be used in the history matching process (Table 1). In order to reduce the reservoir flow simulation CPU run time, the initial model is upscaled laterally by a factor of 4, such that its vertical heterogeneity is preserved and the material balance in the model is conserved so as to maintain the characteristics of the field geology. Also, the binary seismic objective function is calculated on the simulation model scale, so the 4D seismic data is arithmetically upscaled to the simulation model scale.

Setting the scene

The initial state of the reservoir and base case conditions of the history matching process are shown in Figures 5 and 6. Figure 5 shows the observed data, the base case model and the initial ensemble of the response parameters (gas production rate and oil production rate) of wells P1 and P2 which have been

selected for this history matching exercise due to their location and availability of historical data. The observed data represents “hard data” measured at the wells, the base case represents our initial model’s production profile, while the initial ensemble represents profiles for the models generated using the Latin Hypercube Experimental Design which encompasses the effects of the defined uncertain parameters. The observed oil production rate and gas production rate of producer well P1 drops continuously for the first 3 years until an improved oil recovery plan is put in place by introducing injector well I5 to provide pressure support as well as water to sweep the oil. This action stabilizes the production rate for the subsequent years. The same trend is observed for producer well P2, however the oil production rate drops continuously for the first 4 years until injector well I6 replaces the inefficient injector well I1. The introduction of injector well I6 boosts and maintains the oil production rate for the subsequent years until it gently declines. The gas production rate of producer well P2 is high for the first 4 years as there is gas exsolution in the reservoir due to poor pressure maintenance, when this is curbed by introducing injector well I6, the gas production rate drops and declines in the subsequent years. The initial 4D seismic data maps, seismic binary gas maps, simulation pore volume weighted gas maps and simulation binary gas maps are shown in Figure 6. The first 3 monitor surveys corresponding to the first 5 years will be used for the history match, while the last three monitor surveys corresponding to the remaining 5 years will be used to analyse the forecast. The areas of mismatch are highlighted using question marks on the simulation binary gas maps as compared to the seismic binary gas maps, and getting both maps to match is the aim of the seismic assisted history matching exercise.

History matching and predictions

To history match to production data only, the seismic data term in the combined objective function will be assigned a value of zero, such that the reservoir models will be constrained to only the historical production data. Nonetheless, the seismic objective function will still be generated and analysed. After history matching to production data only, the updated production profile and gas distribution are shown in Figure 7 and Figure 8 respectively. Figure 7 shows the production profiles of the updated models (in dark blue colour), and indeed we see an improved match to the observed data as compared to the initial ensemble (in light blue colour). Figure 8 shows the updated simulation binary maps compared to the seismic binary maps with the question marks highlighting areas of minimal improvement on the updated maps even though the model was not constrained to the seismic data. Figure 9 shows the histograms of selected converging parameters, where the critical gas saturation value tends towards a low value of 1.5%, the horizontal permeability multiplier is about 1.2, and the vertical permeability multiplier is marginally less than 1.0. The low value of the critical gas saturation enables gas mobility quite early, hence the minimal presence of gas in the reservoir model, while the permeability multipliers improve fluid flow.

To history match to seismic data only, the production data term in the combined objective function will be assigned a value of zero, such that the reservoir models will be constrained to only the observed seismic data. Nonetheless, the production data objective function will still be generated and analysed.
After history matching to 4D seismic data only, the updated production profile and gas distribution are shown in Figure 10 and Figure 11 respectively. Figure 10 shows the production profiles of the updated models (in dark blue colour), and since it was not constrained to production data the match is not ideal. Figure 11 shows the updated simulation binary gas maps compared to the seismic binary maps with the question marks highlighting areas of positive improvement; indeed the model predicts more gas as expected. Figure 12 shows the histogram of the parameters, where the critical gas saturation value tends towards a value of 4.5%, the horizontal permeability multiplier is about 2.0, and the vertical permeability multiplier is less than 1.0. The high value of the critical gas saturation prevents early gas mobility, hence the presence of more gas in the reservoir model.

To history match to both production data and seismic data, their combined objective function is normalized such that the effect of the production data and seismic data are equal, and that at the beginning of the history match, the combined misfit is a value of one. After history matching to both production data and 4D seismic data, the updated production profile and gas distribution are shown in Figure 13 and Figure 14 respectively. Figure 13 shows the production profiles of the updated models (in dark blue colour) and there is an improvement, while Figure 14 shows the updated simulation binary maps compared to the seismic binary maps with the question marks highlighting areas of improvement. Figure 15 shows the histogram of the parameters, where the critical gas saturation value tends towards a value of 3.5%, the horizontal permeability multiplier is about 1.4, and the vertical permeability multiplier is less than 1.0.

Discussion and Conclusions

It has been demonstrated that constraining the reservoir simulation model to a variety of data (4D seismic data, production data, both) affect the updated parameters differently. The permeability multipliers and critical gas saturation reasonably converged in all scenarios, while the volumetric parameters (porosity, net to gross) remained relatively unconstrained. In order to have a better grasp on this analysis, we plot the objective function and uncertainty for the scenarios as shown in Figure 16. These have been normalized to a value of 100 and 1 for easy comparison. It is observed that when matching to well production data only, the production data objective function and uncertainties are low, but the seismic data objective function and uncertainties are high; and that when matching to seismic data only, the seismic data objective function and uncertainties are lower, but the production data objective function and uncertainties are higher; however when matching to both the production data and seismic data, the production data and seismic data objective function and uncertainties reduces (Walker and Lane, 2007). We go further to analyse the forecasting capabilities of these scenarios and models, by comparing the updated models prediction with the initial model predictions using the combined objective function (Table 2). It is found that matching to production data only gives a 35% percent improvement, matching to 4D seismic only gives a 17% improvement, while matching to both production data and 4D seismic data gives a 42% improvement.

This study proposes a quick look reservoir management approach, where 4D seismic data and production data are used to update the reservoir simulation model without having to apply a complex full physics seismic modelling workflow. The Hamming distance metric which is invariant to small deformations and has an inherent robustness to noise is used to integrate the 4D seismic data with the production data, and has shown its potential of being a useful tool.

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Figures

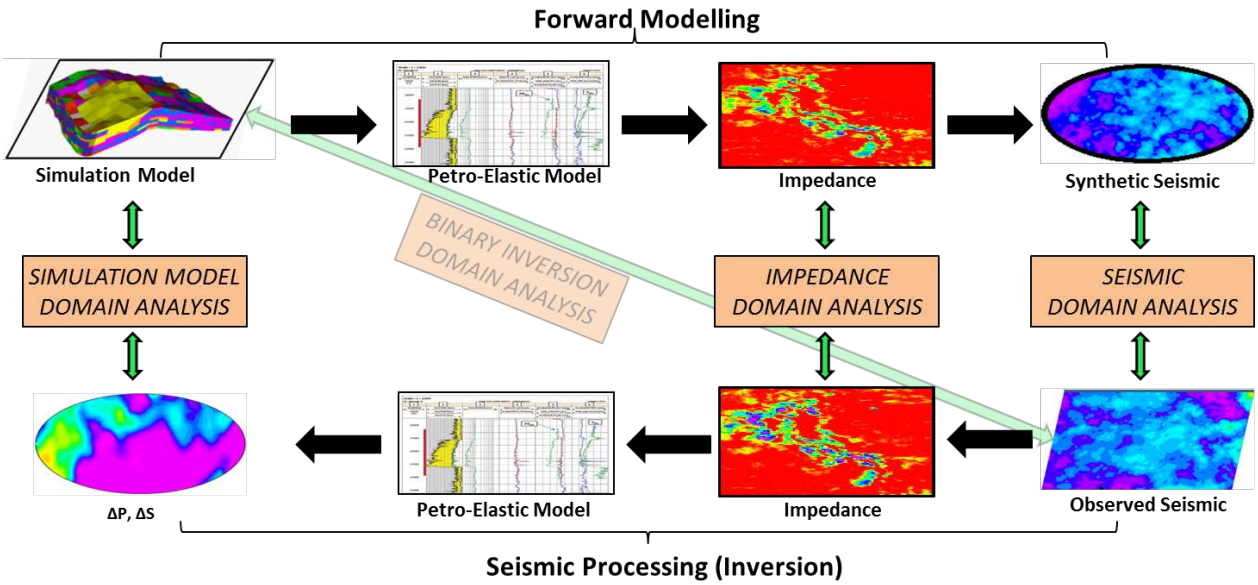

Figure 1 The different domains at which seismic history matching can be explored – the simulation model domain, the impedance domain, and the seismic domain. We propose the binary inversion domain as a quicklook reservoir management tool

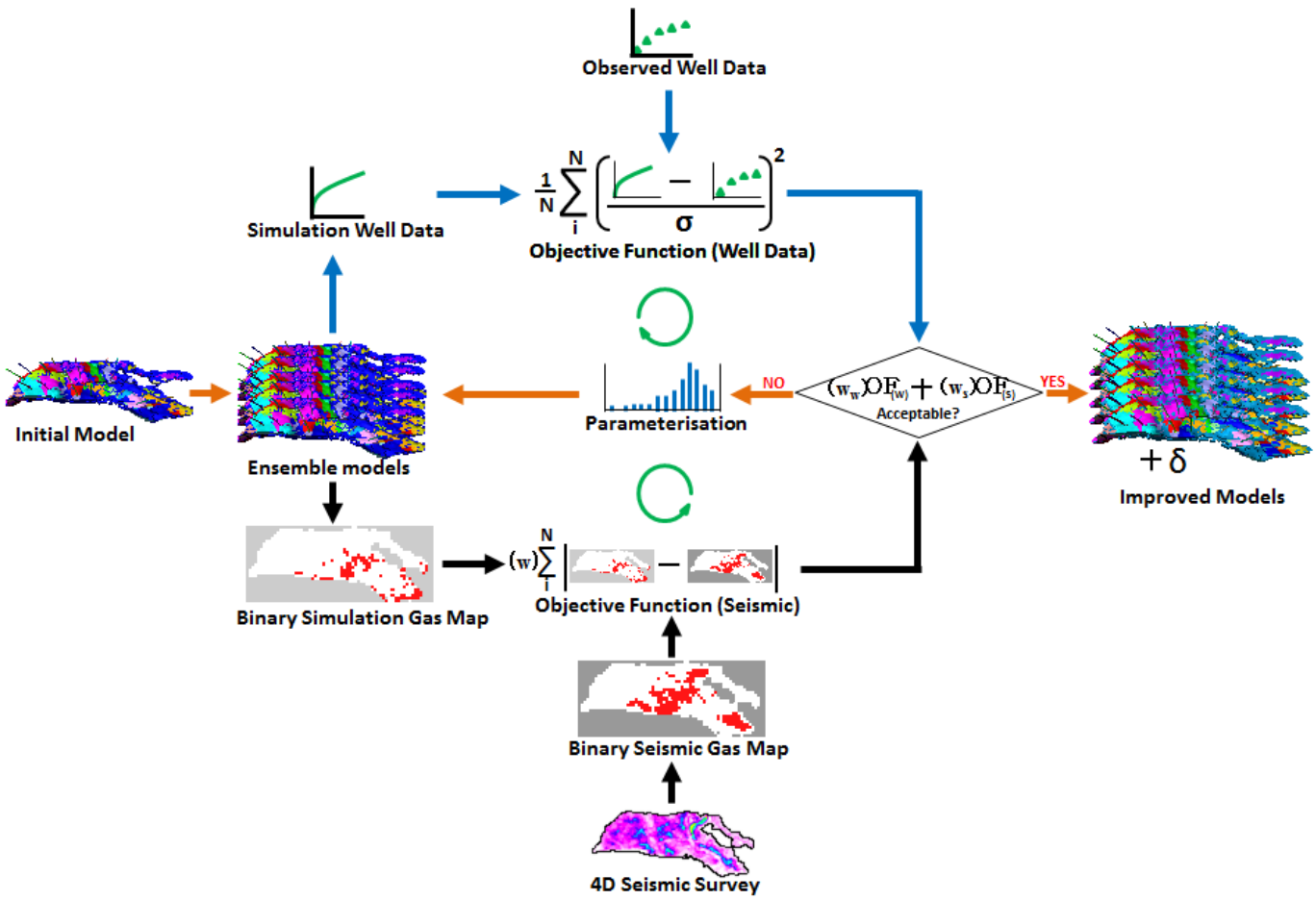

Figure 2 Seismic Assisted History Matching Workflow - combining the production data with the time-lapse seismic data. The blue arrows (upper part) highlight the production history match loop; the black arrows (lower part) highlight the seismic history match loop; the orange arrows (middle part) showcases their individual or combined path; while the green arrows (circular arrows) shows the direction of the loop.

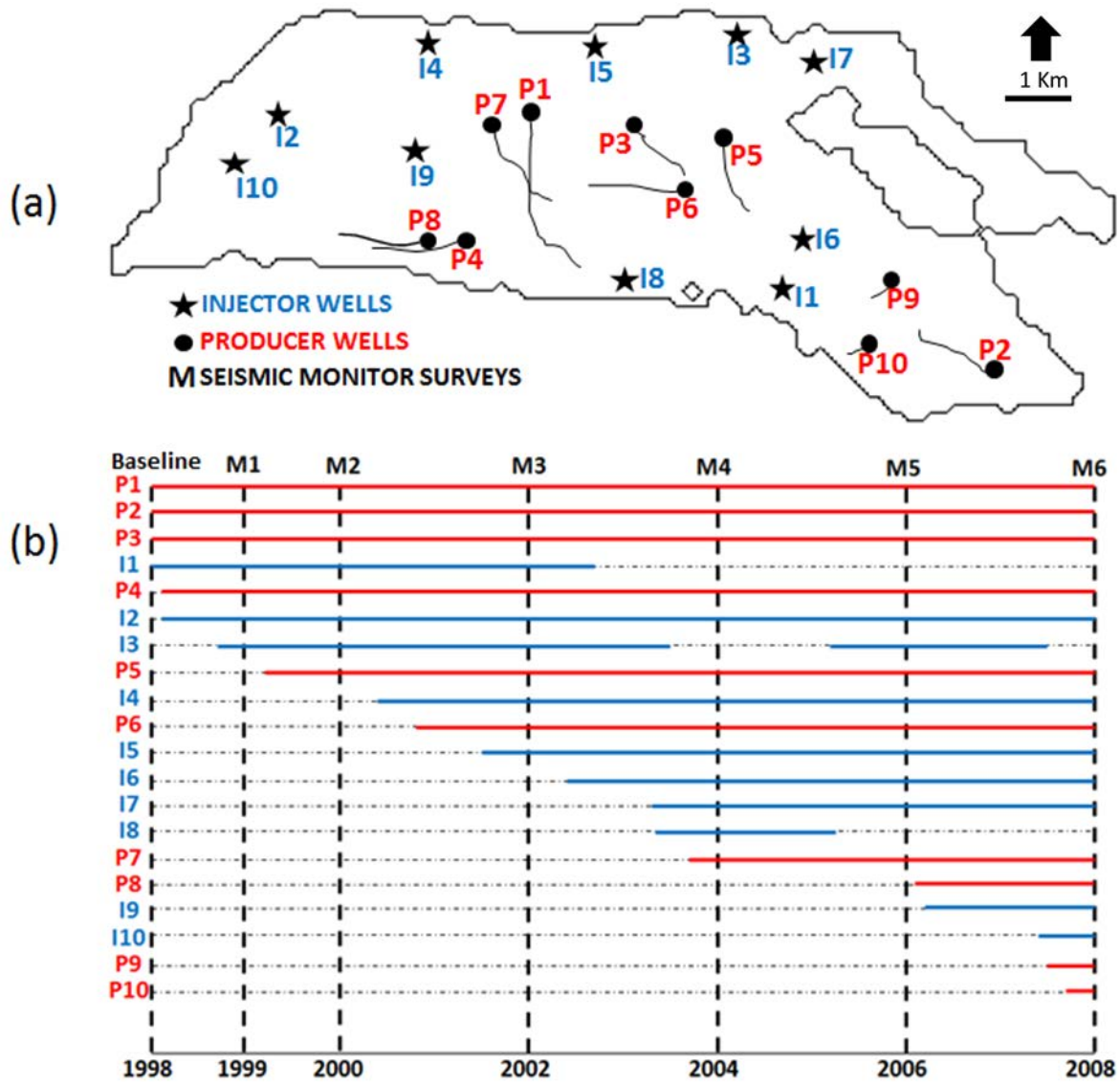

Figure 3 (a) Outline of the reservoir and the position of the producers and injectors. The solid stars and circles correspond to the well TD for the injector wells and producer wells respectively. (b) Timelines of activity for the wells in our chosen sector relative to our monitor seismic data (M1 to M6) surveys. (Obidegwu and MacBeth 2014)

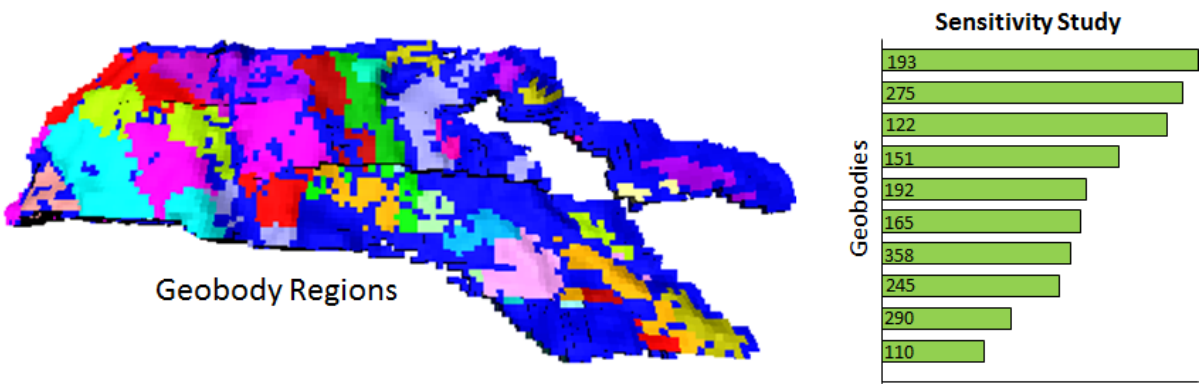

Figure 4 The image on the right shows the different geobody regions, while the figure on the left shows the relative sensitivity of the numbered geobodies to the combined seismic data and production data objective function

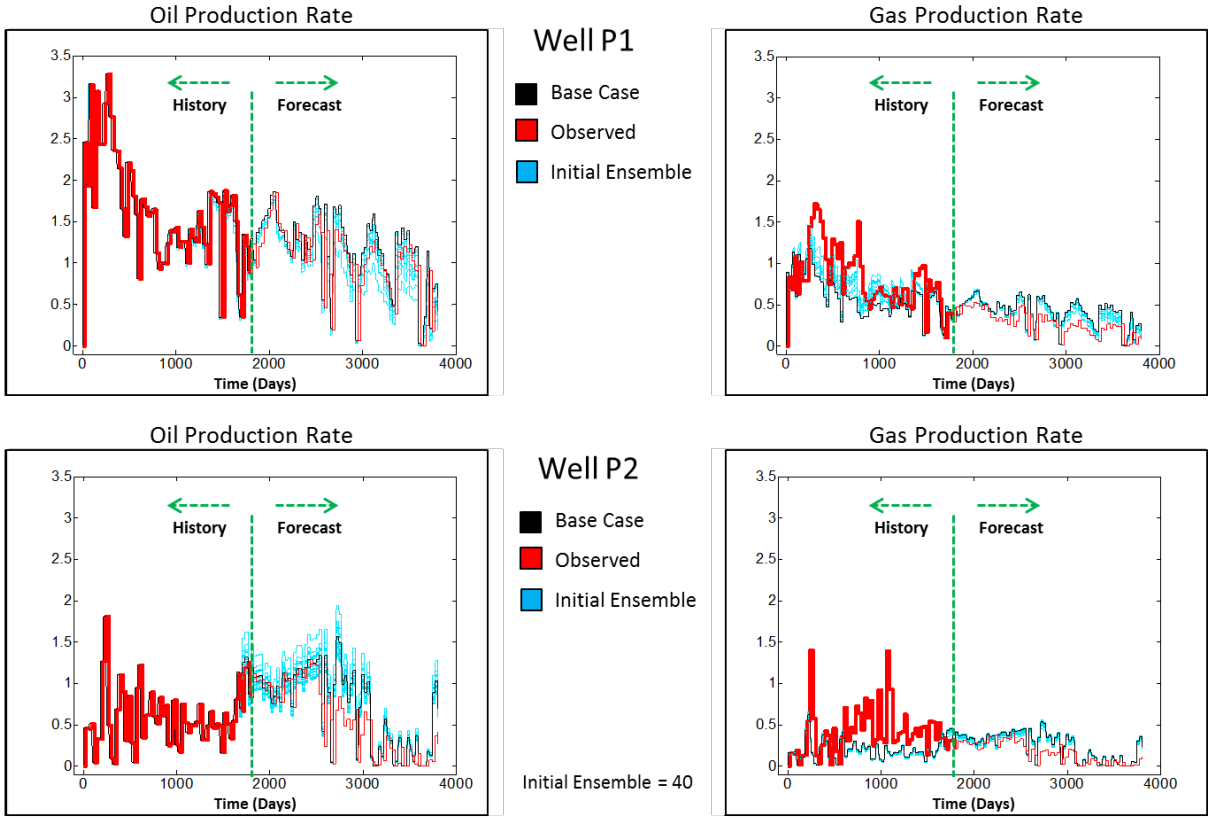

Figure 5 Normalised production profiles (gas production rate and oil production rate) of wells P1 and P2

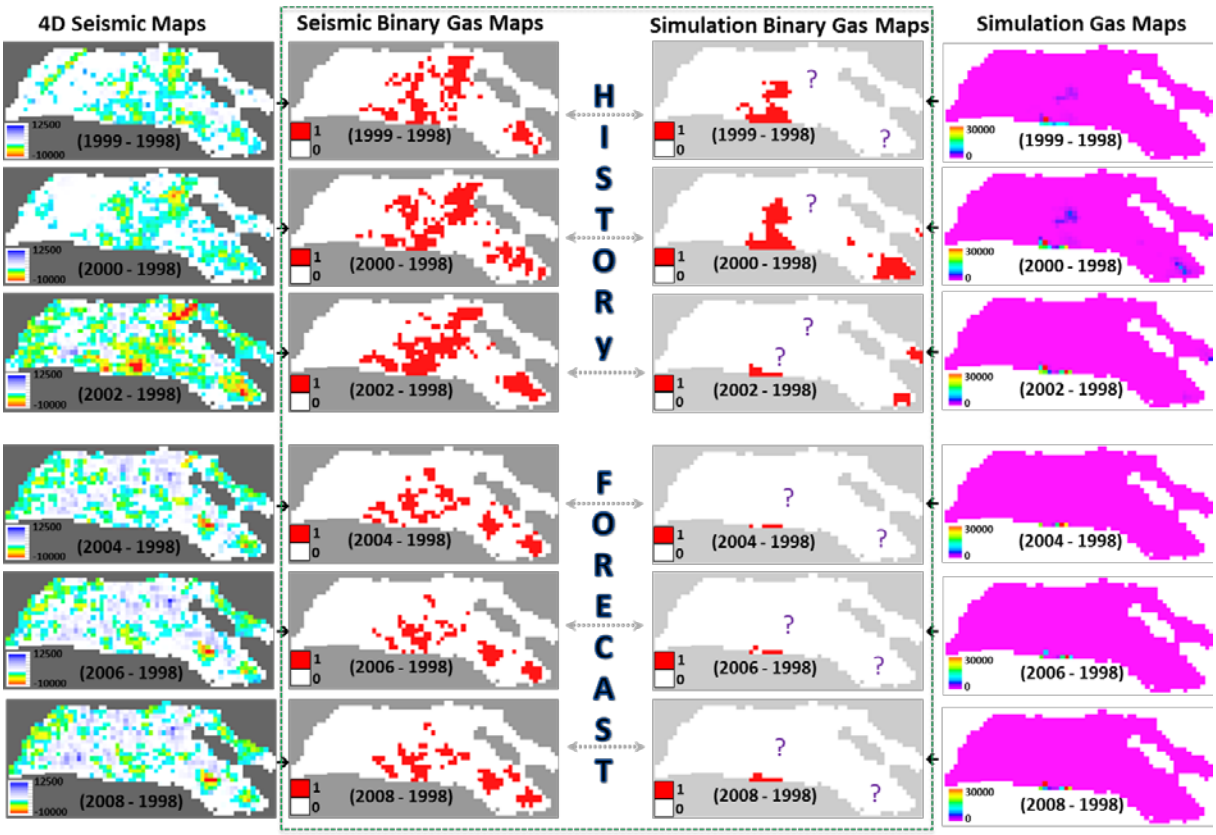

Figure 6 The initial simulation binary gas maps compared to the seismic binary maps highlighting areas of mismatch. The first 3 monitor surveys (the first 3 rows) will be used for the history matching exercise, while the last 3 monitors (last 3 rows) will be used for the forecasting analysis.

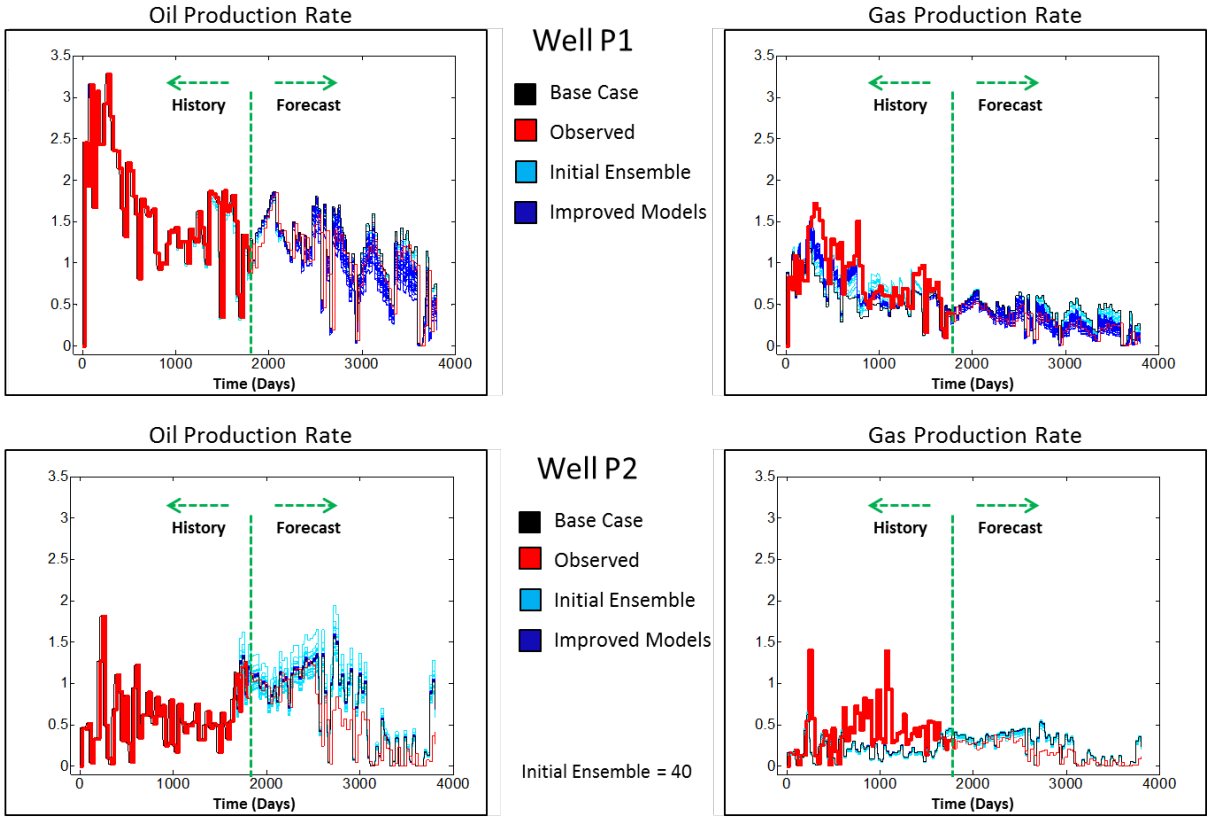

Figure 7 Normalized production profiles (gas production rate and oil production rate) of wells P1 and P2 (History matched to production data only)

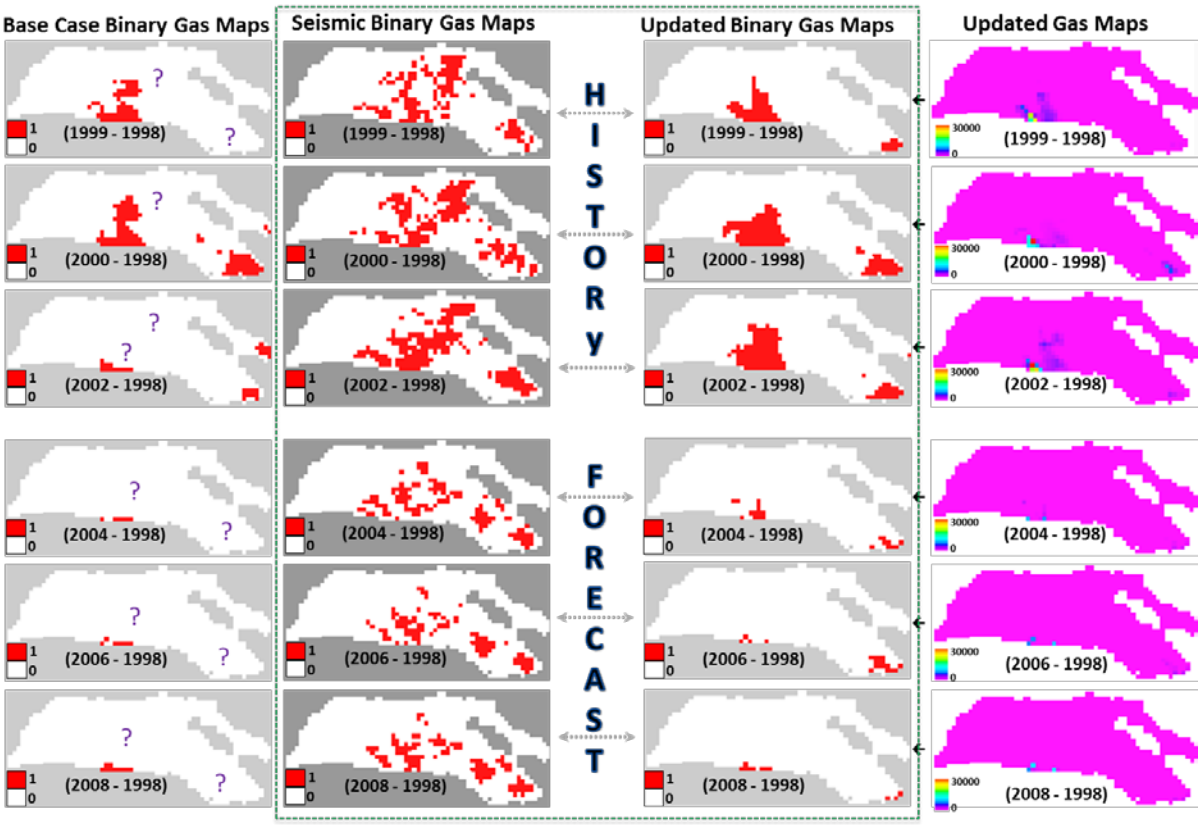

Figure 8 The updated simulation binary maps compared to the seismic binary maps highlighting areas of improvement (History matched to production data only)

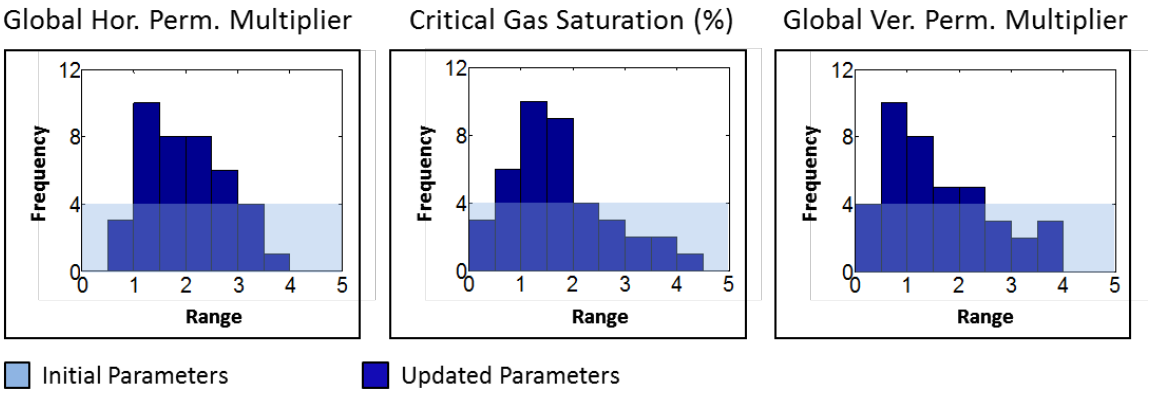

Figure 9 Initial and updated parameters (History matched to production data only)

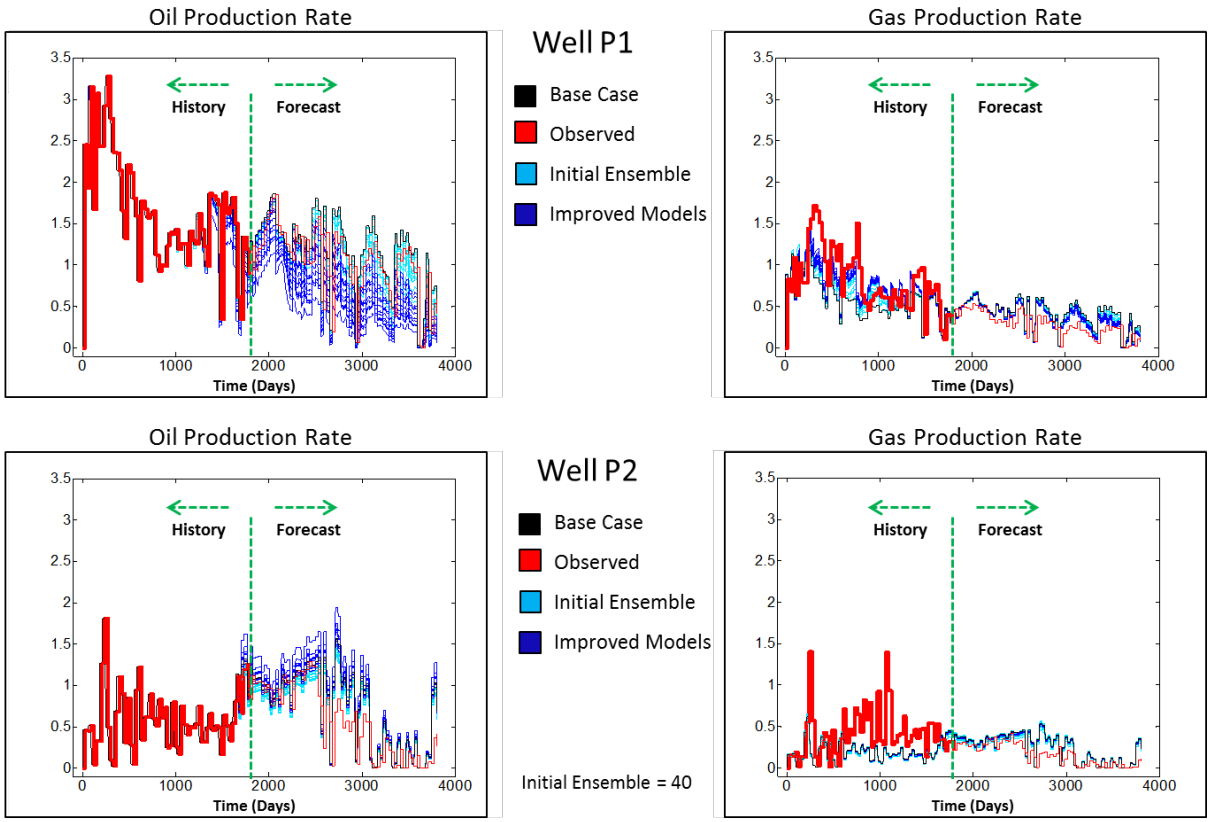

Figure 10 Normalised production profiles (gas production rate and oil production rate) of wells P1 and P2 (History matched to seismic data only)

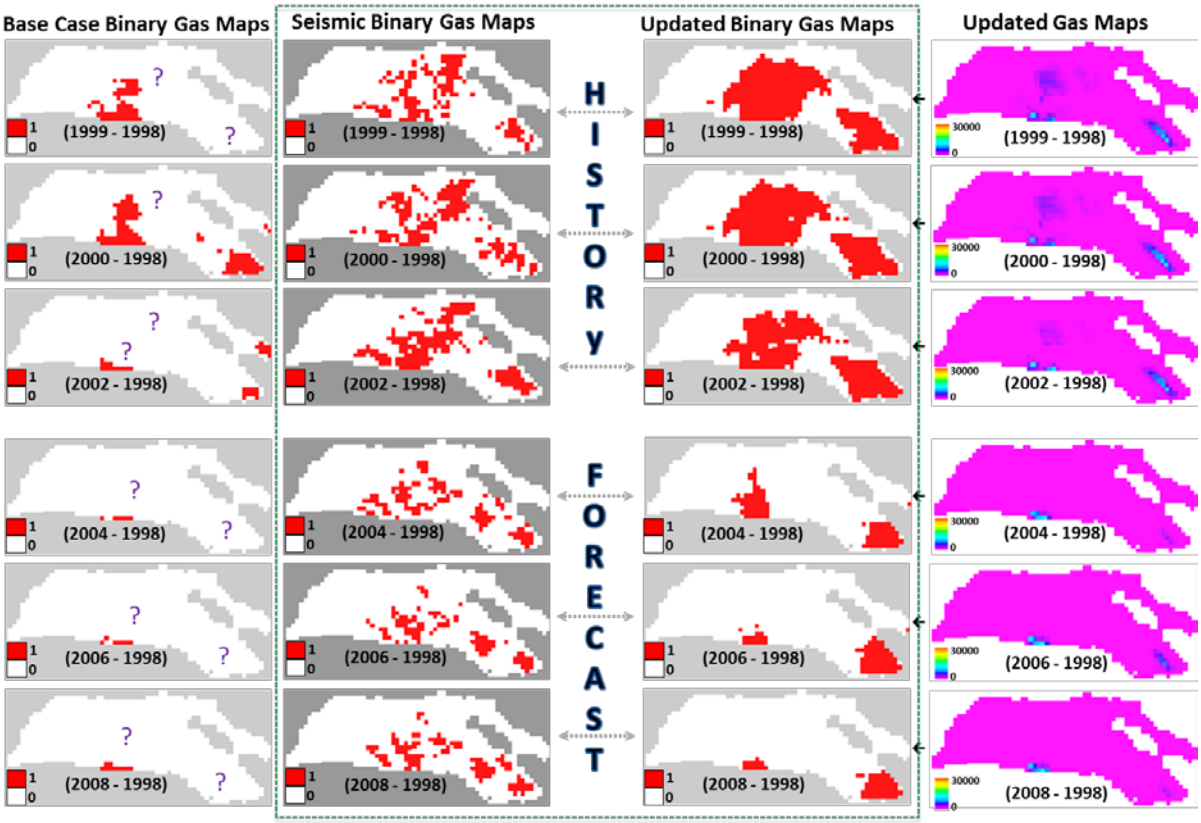

Figure 11 The updated simulation binary maps compared to the seismic binary maps highlighting areas of improvement (History matched to seismic data only)

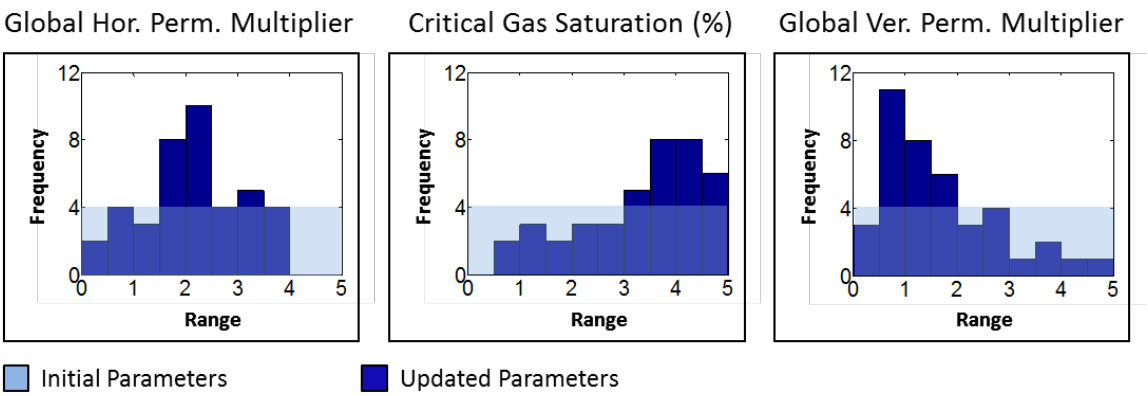

Figure 12 Initial and updated parameters (History matched to seismic data only)

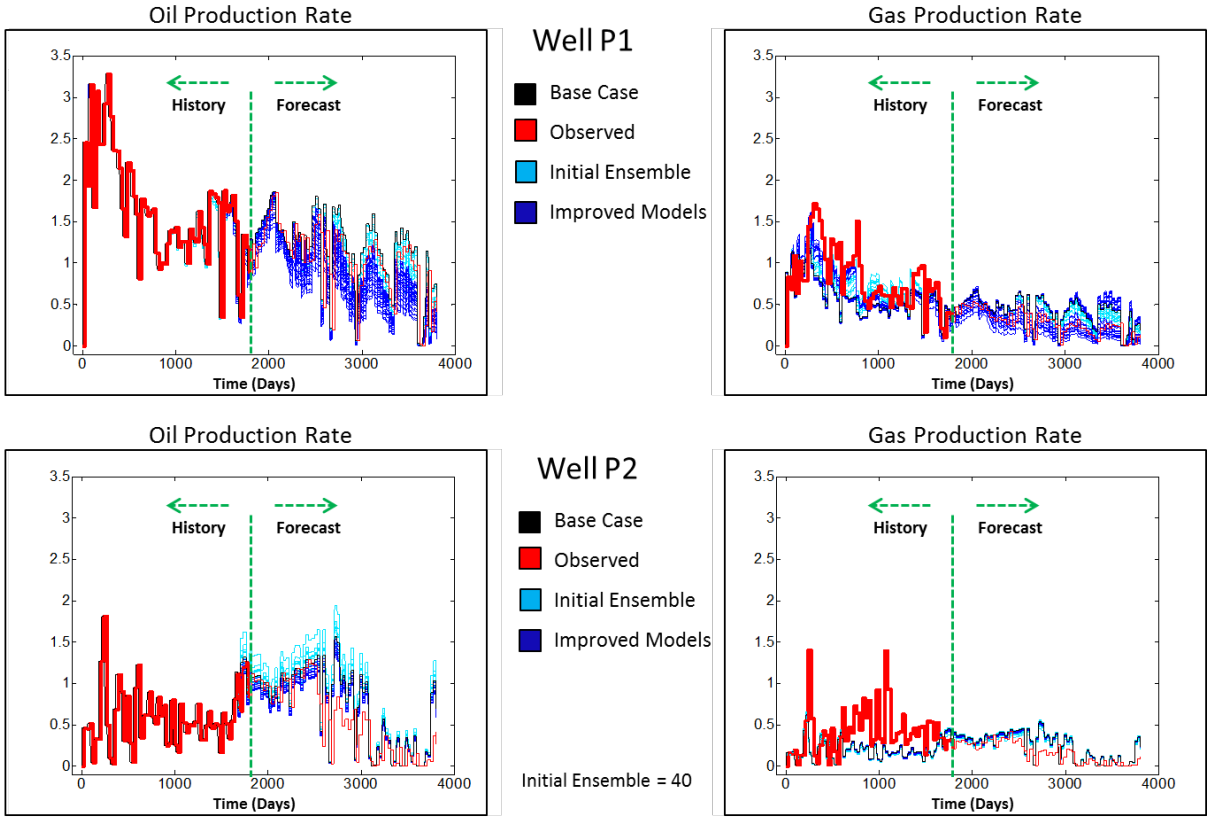

Figure 13 Normalised production profiles (gas production rate and oil production rate) of wells P1 and P2 (History matched to production data and seismic data)

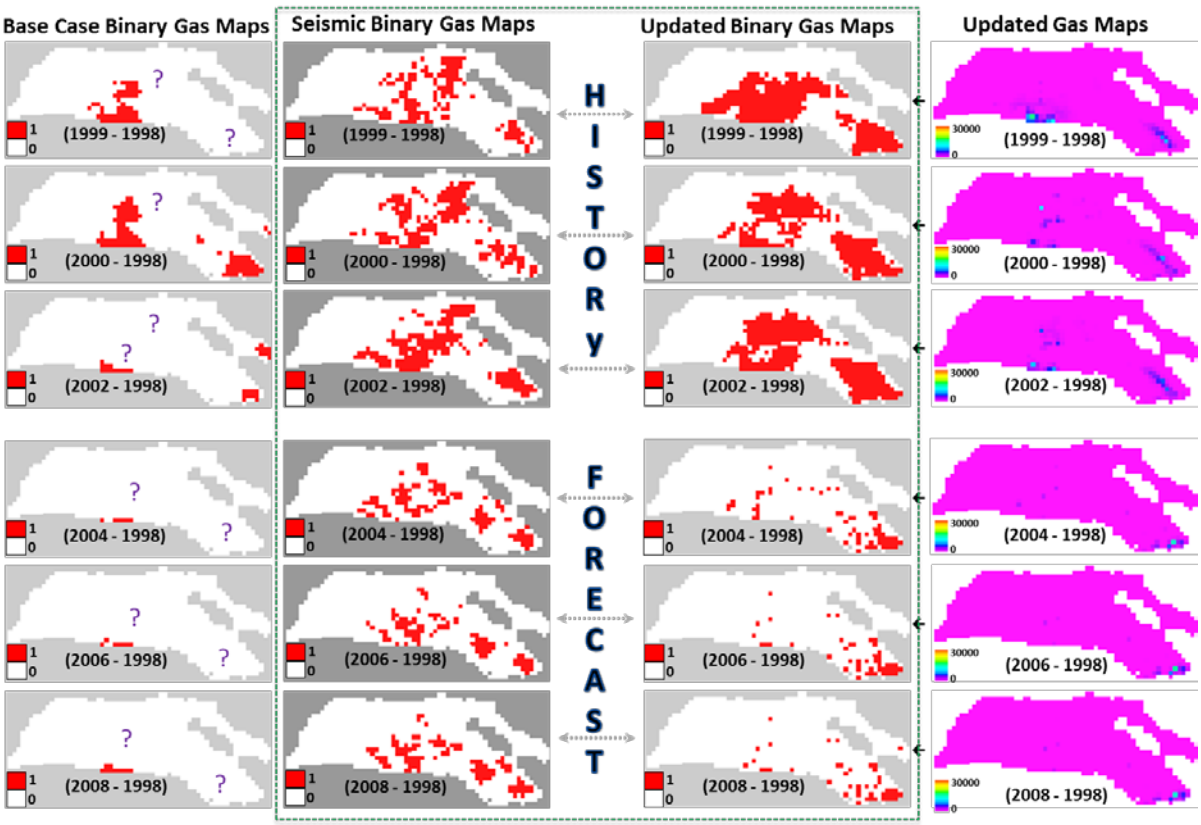

Figure 14 The updated simulation binary maps compared to the seismic binary maps highlighting areas of improvement (History matched to production data and seismic)

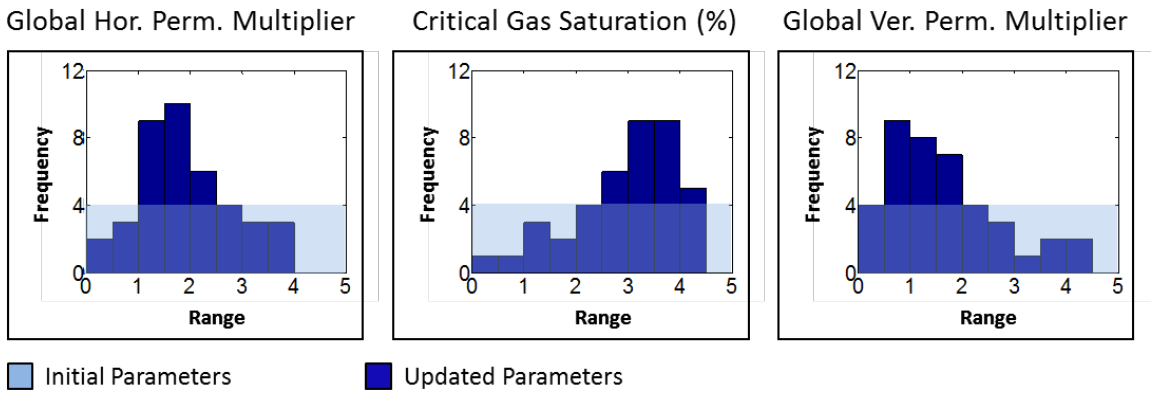

Figure 15 Initial and updated parameters (History matched to production data and seismic data)

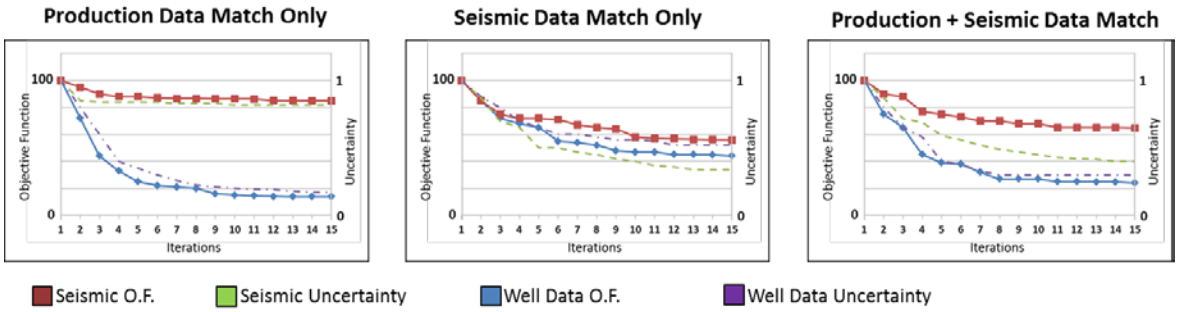

Figure 16 Objective Function and Uncertainty - The dotted lines represent the uncertainty and have their scale at the right hand side, while the continuous lines represent the objective function. The blue line represents the production data objective function, while the red line represents the seismic objective function. The purple dotted line represents the production data uncertainty, while the green dotted line represents the seismic uncertainty.

TABLES

PARAMETERS	NUMBER	LOWER LIMIT	START VALUE	UPPER LIMIT
Global NTG Multiplier	1	0.35	1	2
Global Perm. Multiplier	3	0.35	1	5
Global Poro Multiplier	1	0.35	1	2
Global Pore Vol. Multiplier	1	0.35	1	2
Transmissibility Multiplier	3	0	1	3
Regional NTG Multiplier	7	0.35	1	2
Regional Perm. Multiplier	14	0.35	1	5
Regional Pore Vol. Multiplier	3	0.35	1	2
Critical Water Saturation	1	0.4	0.428	0.5
Critical Gas Saturation	1	0	0.001	0.05
TOTAL NO. OF PARAMETERS	35			

Table 1 Model Parameterization for history matching the reservoir. The global parameters are parameters that are perturbed over the entire reservoir, while the regional parameters are parameters that are perturbed over selected regions/geobodies

	Forecast Improvement
Production Data Only	34.60%
Seismic Data Only	17.31%
Production & Seismic	41.65%

Table 2 Forecast improvement using the combined objective function, with respect to the initial model predictions