Adaptive multi-scale ensemble-based history matching of seismic-derived models

Théophile Gentilhomme, University of Lorraine/Hampson-Russell – CGG, Dean Oliver, CIPR, Trond Mannseth, CIPR/Bergen University, Rémi Moyen, Hampson-Russell – CGG, Guillaume Caumon, University of Lorraine, and Philippe Doyen, Hampson-Russell – CGG

Abstract

We present a new history matching approach designed for highly detailed seismic derived prior models. An ensemble-based optimization method is used to integrate production data and quantify associated uncertainties. An adaptive multi-scale wavelet parameterization is applied to stabilize the inversion and preserve the compatibility of history matched models with seismic data by first modifying a few low frequency parameters and then progressively allowing more important updates on a limited number of sensitive parameters of higher resolution. We show numerically that this adaptive multi-scale method avoids unnecessary updates and reduces noise, which are typically observed in standard ensemble-based methods when using a small ensemble. The new method is validated using a synthetic example. We observe that the final realizations better preserve the spatial distribution of the prior models, are less noisy and also fit the production data better than the realizations updated using a standard grid-block method.

Introduction

Simultaneous inversion of 3D seismic and production data is generally difficult, due to a number of factors such as the high dimensionality of the seismic inverse problem compared to the history matching problem, intrinsic differences about the underlying scale of observation and differences in ways models are parameterized. For these reasons, seismic and production data may be integrated sequentially: an initial petrophysical geo-model is built using seismic information, usually through pre-stack seismic inversion and then is perturbed to match historic production data. For this second step, ensemble-based methods of optimization (Aanonsen et al., 2009) have become popular thanks to their flexibility, computational efficiency and ability to match dynamic data using a wide range of parameters and quantify posterior uncertainties. A global gradient is statistically computed from an ensemble of realizations and is used to update each individual member. However, for high dimensional problems, the size of the ensemble is limited as a full fluid flow simulation needs to be run for each member. For this reason, the resulting gradient may be noisy and leads to spurious updates which will damage important geological seismic-driven features of the prior models and significantly reduce the variability of the ensemble. Localization (Chen and Oliver, 2010-b) is often used to limit these effects by limiting updates to predefined areas. However, it is not trivial to characterize these areas. Furthermore, parameters outside the localization do not benefit from the assimilation of the production data.

Here, we propose a new adaptive multi-scale history matching approach which preserves the prior information and stabilizes the inversion process by sequentially selecting a limited number of parameters localized in sensitive areas.

Different methods of multi-scale parameterization are found in the petroleum literature (Chavent and Bissel, 1998; Lu and Horne, 2000; Grimstad et al., 2003; Ben Ameur et al., 2002; Mannseth, 2006; Jafarpour and McLaughlin, 2008; Bhark et al., 2011). Generally, the optimization is started using a coarse parameterization, which is successively refined. The major benefit of this approach is that the coarse version of the problem is better defined and generally more linear than in a fine-scale model, which helps to avoid local minima and over-parameterization.

In this work, we re-parameterize the history matching problem using second generation wavelets (Swelden, 1997). Wavelet functions are localized both in space and frequency. Thus, the problem can be adapted depending on the local sensitivity of the parameters: sensitive areas are updated mainly based on the data mismatch, whereas insensitive areas are more constrained by the prior model. However, unlike the usual localization, global updates are performed through the large scale parameters. Moreover sensitive zones are automatically chosen by analyzing the optimization results. A synthetic test case is used to demonstrate the advantages of our approach compared to a standard grid-block-based parameterization method.

Re-parameterization using 2nd generation wavelets

The discrete wavelet transform is a linear transformation which decomposes the signal into different frequencies. Its basis is composed of finite support functions called wavelets. Each wavelet is associated with a frequency range and a finite localization in space. This property is used in image compression where high frequencies are only included where they bring important information, for example to characterize a sharp color variation. Since images or reservoir properties are generally spatially correlated, only a few wavelet coefficients are needed to obtain a good approximation of the original signal. For this reason, wavelet-based re-parameterization of an ill-posed inverse problem is interesting as it yields a significant reduction in the number of inverted parameters. However, unlike image compression in which coefficients are selected based on their impact on the visual aspect of an image, our adaptive history matching method selects additional frequencies only where they have an important impact on the flow response.

Standard first generation wavelets (Mallat, 1989) are built from translations and dilatations (by a factor of two) of a generating function called the mother wavelet. Because of translation-dilatation invariance, first generation wavelets are usually only applicable to grids of dimensions equal to a power of two. For this reason, we use second generation wavelets which can be applied to any grid and are flexible (Gentilhomme et al., 2012). Second generation wavelets lack the translation and dilatation invariance property. Instead, they are adapted to their spatial localization, but keep the same space-frequency localization property as traditional wavelets. In this work, we use a quadratic wavelet based on a polynomial interpolation of degree two, which can be seen as an improved Haar wavelet (Swelden and Schröder, 1996).

Optimization with reduced number of parameters

The Levenberg-Marquardt ensemble randomized maximum likelihood (LM-enRML) (Chen and Oliver, 2012-a; Chen and Oliver, in review) is an iterative Levenberg-Marquardt method which computes a global gradient using an ensemble of realizations. The global gradient is used to update simultaneously several realizations which are members of the ensemble (Gu and Oliver, 2007). The initial ensemble can be constructed using realizations derived from seismic stochastic inversion (Buland and Omre, 2003; Moyen and Doyen, 2009) and deemed to be representative of the seismic inversion uncertainty. Each ensemble member (vector of parameters, i.e. cell porosities, permeabilities…) $\mathbf{m}$ of size n is transformed into wavelet coefficients. The optimization is then performed on a subset of selected coefficients $\boldsymbol{\gamma}_{\text{opt}}$ of size $n_{opt} \leq n$, such that:

$$\begin{bmatrix}\boldsymbol{\gamma}_{\text{opt}} \\ \boldsymbol{\gamma}_{\overline{\text{opt}}}\end{bmatrix} = \mathbf{W}.\mathbf{m} \quad (1)$$

where **W**, **m**, $\boldsymbol{\gamma}_{\text{opt}}$ and $\boldsymbol{\gamma}_{\overline{\text{opt}}}$ correspond to the (n x n) wavelet transform matrix, the (n x 1) initial vector of grid-block values (i.e. porosity, permeability), the (n_{opt} x 1) vector of wavelet coefficients included in the optimization and its ((n – n_{opt}) x 1) complement vector respectively. During optimization, which is constrained by a number of n_d data, the global gradient is obtained from the (n_d x n_{opt}) sensitivity matrix **G** which is computed from the n_e ensemble members by solving:

$$\Delta\mathbf{D} = \mathbf{G}.\Delta\boldsymbol{\Gamma} \quad (2)$$

Each column of the (n_d x n_e) $\Delta\mathbf{D}$ matrix and the (n_{opt} x n_e) $\Delta\boldsymbol{\Gamma}$ matrix store, for each realization, the deviation of the predicted data and deviation of the wavelets coefficients from the ensemble means, respectively. Because of the reduction in the number of parameters ($n_{opt} \leq n$), the computation of **G** is relatively fast. Finally, the perturbation of the parameters can be represented as:

$$\delta\boldsymbol{\gamma}_{\text{opt}} = \underbrace{-\frac{1}{\lambda+1}\left(\boldsymbol{\rho} \circ \delta\boldsymbol{\gamma}_{pr} + \boldsymbol{K}.\boldsymbol{G}\left(\boldsymbol{\rho} \circ \delta\boldsymbol{\gamma}_{pr}\right)\right)}_{\textbf{Prior term}} \underbrace{- \boldsymbol{K}.\delta\boldsymbol{d}}_{\textbf{Mismatch term}} \quad (3)$$

Where $\lambda + 1$ is the Levenberg-Marquardt damping parameter (scalar), $\boldsymbol{K}$ is a matrix similar to the Kalman gain (Chen and Oliver, in review), $\delta\boldsymbol{\gamma}_{pr}$ is the deviation from the prior (n_{opt} x 1) vector, $\delta\boldsymbol{d}$ is the data mismatch (n_d x 1) vector, $\boldsymbol{\rho}$ is a (n_{opt} x 1) vector of values in $[0, \lambda + 1]$ weighting the contribution of the prior during the optimization and $\circ$ represents the Schur product.

Although we optimize only a subset of the coefficients, all coefficients are used to reconstruct the properties used by the flow simulator. However, it is generally useful to attenuate the impact of non-selected coefficients (mostly high frequencies) on the flow response in order to simplify the objective function and avoid local minima. Accordingly, the high frequencies are smoothed at the beginning of the optimization. Thanks to the compression property of the wavelet basis, all important features are still preserved, as illustrated in Figure 1.

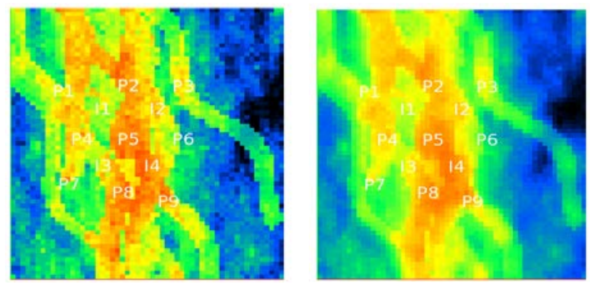

Figure 1: Original porosity realization (left) and its smoothed version (right) used at the beginning of the multi-scale approach.

Due to the smoothing of the realizations, some high frequency prior information is lost. During the optimization process, this information is reintroduced at the update stage (equation 3) thanks to the adaptive prior constraint $\boldsymbol{\rho} \circ \delta\boldsymbol{\gamma}_{pr}$. Since the wavelet coefficients are localized in space, the prior constraint can be adapted depending on the localization.

Adaptive multi-scale approach

Adaptive multi-scale methods are commonly used in history matching (Chavent and Bissel, 1998; Grimstad et al., 2003; Lu and Horne, 2000; Bhark et al., 2011) in order to adapt the parameterization to the data, stabilize the inversion and avoid over-parameterization. Although not formally proven, multi-scale optimization is considered to help avoid local minima (Liu, 1993; Mannseth, 2006; Chavent, 2009). Generally, these methods start by optimizing a limited number of large scale coefficients. The parameterization resolution is then increased by analyzing the results of the optimization step. In this work, we propose an adaptive approach based on LM-enRML optimization using wavelet parameterization. An overview of this method is given in Figure 2. The main central loop corresponds to iterations through the different resolutions. Before entering the loop (step 0), some low resolution wavelet coefficients are selected depending on the confidence we have in the prior model. In the first step (step 1), these parameters are optimized using the LM-enRML algorithm. Then (step 2), the algorithm checks whether iterations should continue. If so, at the next step (step 3), new parameters corresponding to the next finer resolution are added. By analyzing the last sensitivity matrix (equation 2), it is possible to identify sensitive parameters at the current resolution. For these sensitive parameters, the prior constraint is kept low (by setting the corresponding values in ρ close to 0) and the data mismatch term will mainly condition their update (equation 3). For the insensitive parameters, more weight is put on the prior constraint such that it controls the parameters update. In this manner, the prior knowledge, which was removed through realizations smoothing, is reintroduced without significantly affecting the objective function. Finally, a new optimization is run with the new parameterization and constraint. This process is repeated until the finest resolution is reached or the mismatch falls within production data uncertainty.

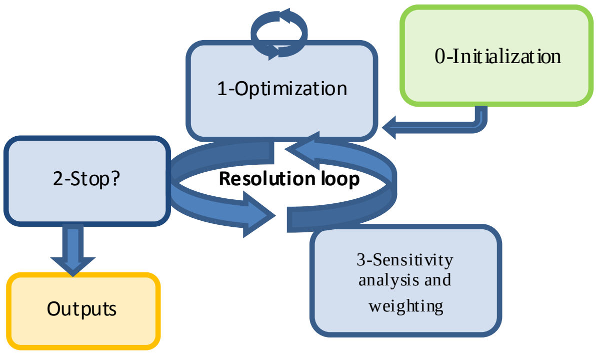

Figure 2: Overview of the adaptive multi-scale approach. (0) Initialize the parameterization. (1) Optimize with the current parameterization. (2) Check stopping criteria. (3) Find sensitive areas and adapt the prior constraint weights $\boldsymbol{\rho}$.

Adaptive refinement

Several techniques of adaptive refinement have been proposed in the context of history matching in order to select the most relevant parameters for lowering the objective function based on its local approximation or gradient analysis (Chavent and Bissel, 1998; Lu and Horne, 2000; Ben Ameur et al., 2002; Grimstad et al., 2003). In this work, we use a sensitivity matrix computed from the last flow simulations using equation 2. However, instead of computing the sensitivity corresponding to the wavelet coefficients, we compute the sensitivity of the scaling coefficients, which correspond to the local averages of the properties (Sweldens and Schröder, 1996). Because the sensitivity matrix computed from an ensemble can be very noisy, a distance-based averaging filter is applied to each row of the sensitivity matrix which can be seen as a (3D) sensitivity map for one data point (Figure 3, left). Then, using all the rows, it is possible to compute a (3D) map of the most sensitive parameters (Figure 3, right) by taking into account all the data. Finally, the corresponding sensitive wavelet coefficients can be identified. This approach is similar to the enKF localization as described in Chen and Oliver (2010-b), where the analysis of the cross-correlation between data and parameters is used to define a prior localization of the Kalman gain (localization for each data point). However, our adaptive multi-scale method has several advantages compared to prior grid block manual localization. (1) The multi-scale approach optimizes a few coarse scale parameters first while preserving all others frequencies. Although it is generally not possible to match the data only using these parameters, the data mismatch can be significantly reduced, thereby limiting the perturbation of the finer frequencies. (2) The multi-scale parameterization allows global updating of the realizations and not only inside predefined areas. Moreover, as the localization is handled by the prior weights $\boldsymbol{\rho}$, updates can still be made if the flow response is found to be very sensitive to parameters localized outside an incorrect localization. (3) Unlike prior localization, our approach provides an adaptive localization, i.e., sensitive area may evolve during the optimization process. (4) Finally, no *a priori* maps need to be created, which can be a difficult task. However, because of the limited size of the ensemble and despite the smoothing of the realizations, the quality of the sensitivity matrix might not be sufficient. In this case, it might be useful to use prior localization maps along with the adaptive refinement.

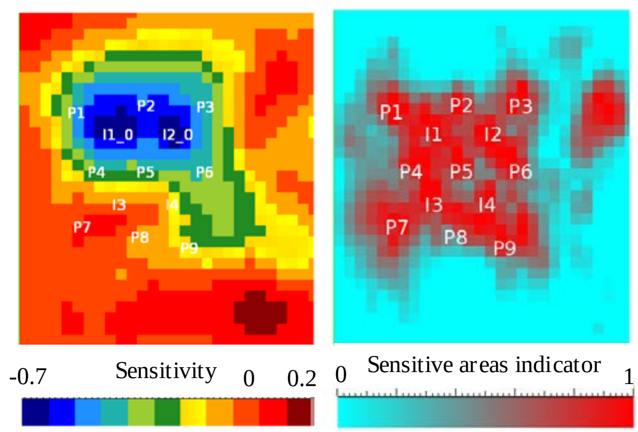

Figure 3: Sensitivity analysis and sensitive areas indicator. Left: Well P2 water cut (at time t) sensitivity map at a coarse resolution. Right: Sensitivity map including all the sensitivity analyses.

Example

History matching using second generation wavelets parameterization and adaptive multi-scale refinement is tested on a two dimensional synthetic case composed of 3355 active cells which are populated by porosity and permeability fields generated from object-based simulation and Sequential Gaussian Simulation. A total of nine producers and four injectors, arranged in a five-spot pattern, are used to generate data representing seven years of production with the porosity and permeability fields displayed in the Figure 4. Water saturations, pressure and gas-oil ratio are used to constrain the inversion of the permeability and porosity fields. Ensemble optimization with the standard full grid-block parameterization and our adaptive multi-scale approach are compared. Quadratic wavelets are used as basis functions in the second case. In both cases, a total number of 15 iterations are performed using an ensemble of 60 realizations generated from object-based simulation.

Results

Figure 5 shows the evolution of the objective function for both cases. With the full grid-block parameterization, the objective function converges faster, but reaches a final mismatch 2.5 times larger than with the wavelet parameterization, suggesting that the latter is less sensitive to local minima.

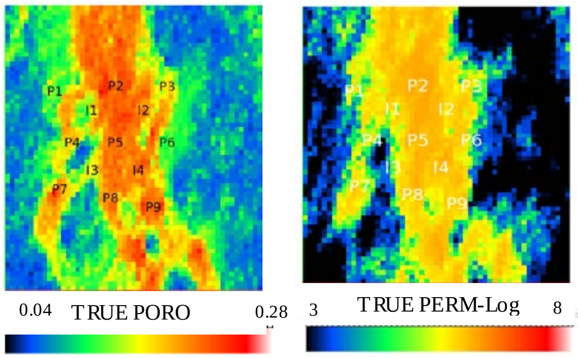

Figure 4: Porosity (left) and log-permeability (right) fields used to generate the synthetic data.

With the adaptive multi-scale approach, a sensitivity analysis (Figure 5, vertical lines) is performed before each introduction of finer resolution coefficients and after the finest resolution is reached. In the latter case, no additional resolutions are added but the sensitive area is extended such that the prior constraint is relaxed. After eight iterations, the two methods have a similar mismatch even if the multi-scale method does not include all the resolutions. After the 9th iteration of the new method, the objective function increases slightly: some high frequencies, removed during the smoothing of the realizations, are reintroduced and a small increase of the mismatch is permitted by the algorithm. This way, the prior information is better preserved and the variability at this resolution increases, which is beneficial for the ensemble as it avoids its collapse.

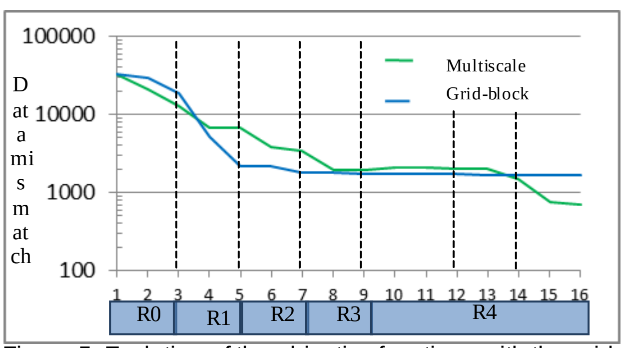

Figure 5: Evolution of the objective functions with the grid-block (blue) and adaptive multi-scale (green) parameterization. The Ri correspond to newly added wavelet coefficient resolutions. Vertical lines indicate sensitivity analysis steps and modification of the prior constraint.

Matches of pressure and water cut for wells P1, P6 and P8 are displayed in Figures 6 to 8. Generally, the pressure match is better using our method while the match of the water cut is not significantly improved compared to the grid-block approach, which might result from the better characterization of the large scale with our method. In order to compare the two methods, the same data set is used to constrain the inversion of each realization. This does not correspond to the original enRML formulation where conditioning data for each realization are sampled from the data distribution (see Gu and Oliver, 2007). This explains why the resulting data spread is quite low.

Figures 9 and 11 show the resulting porosity and permeability fields after assimilation of production data using the two methods. Comparison of the true model (Figure 4) and the final realizations shows that, in both cases, the integration of production data enables the characterization of important flow structures, especially close to the wells. However, away from the wells, the multi-scale approach avoids the introduction of spurious structures that are not present in the true model. Moreover, the final realizations generated using the multi-scale approach better preserve the spatial structure of the prior models, are less noisy and also fit the production data better than the realizations constructed using the standard grid-block approach. Average cell-by-cell perturbations from prior maps, computed from the entire ensemble, are shown in Figures 10 and 12. The multi-scale approach yields a better match while minimizing both the amplitude and spatial frequency of the perturbations. Moreover, important modifications are mainly localized in areas around the wells whereas they are spread over the entire model in the grid-block approach.

Conclusions

The adaptive multi-scale method based on second generation wavelets parameterization appears to be useful for stabilizing the inversion and avoiding spurious effects in ensemble-based optimization methods. In the synthetic example presented here, a better match and preservation of the prior are obtained with our approach compared to a standard enRML method. The multi-scale approach and the smoothing of the realizations tend to make the problem more linear, which helps avoid local minima. At the same time, the adaptive prior constraint manages to efficiently incorporate prior knowledge (seismic-derived information) without damaging the advantages of the multi-scale approach, which helps maintain a sufficient variability in the ensemble.

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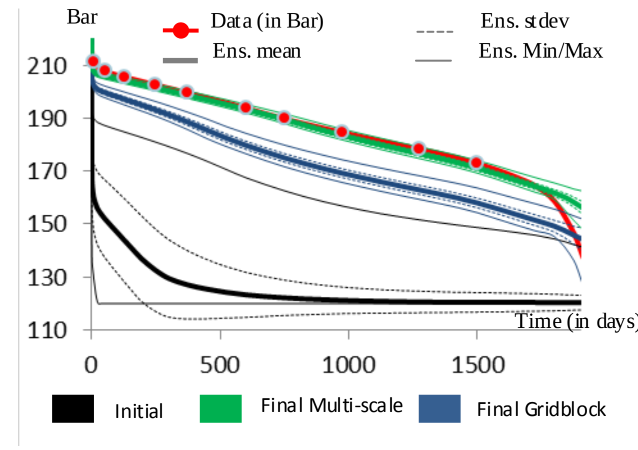

Figure 6: Bottom-hole pressure match at well P1.

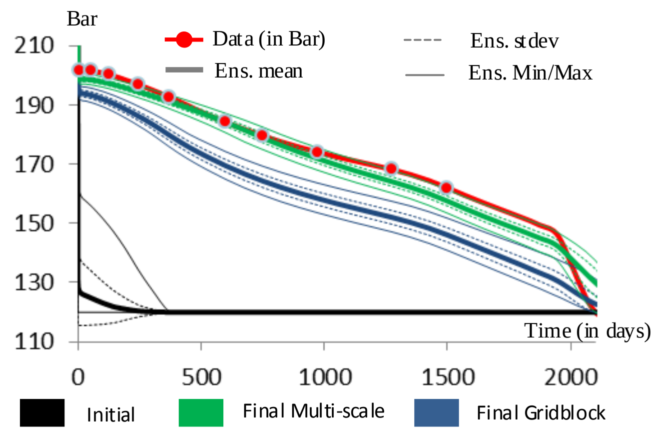

Figure 7: Bottom-hole pressure at well P6

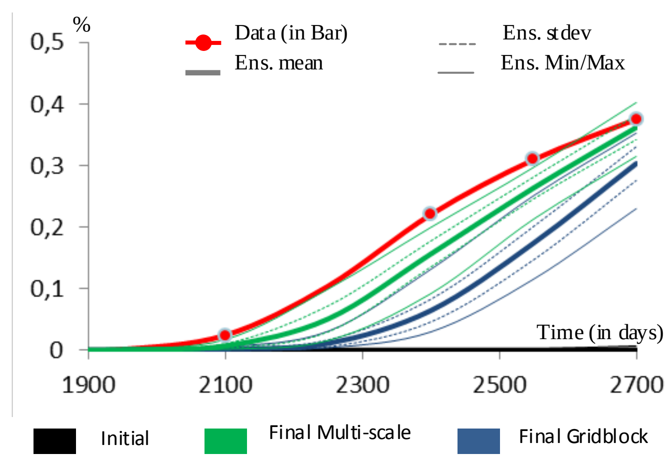

Figure 8: Water cut at well P6.

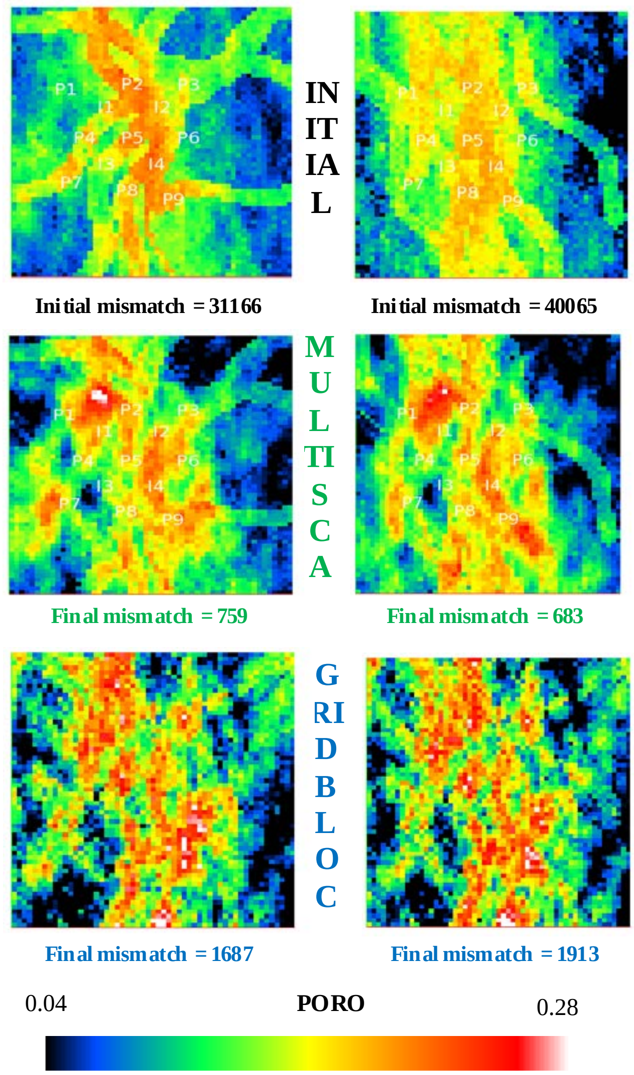

Figure 9: Porosity realizations before and after optimization. Top row: initial realizations and their mismatches. Middle row: updated realizations using the multi-scale method and their mismatches. Bottom row: updated realizations using standard grid-block parameterization and their mismatches.

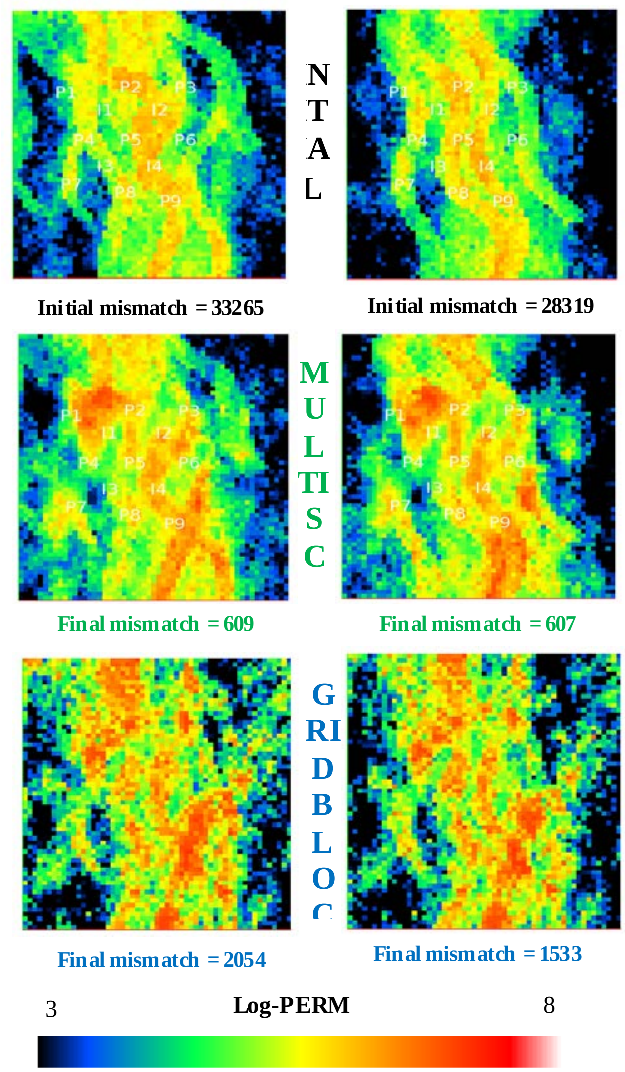

Figure 11: Permeability realizations before and after optimization. Top row: initial realizations and their mismatches. Middle row: updated realizations using the multi-scale method and their mismatches. Bottom row: updated realizations using standard grid-block parameterization and their mismatches.

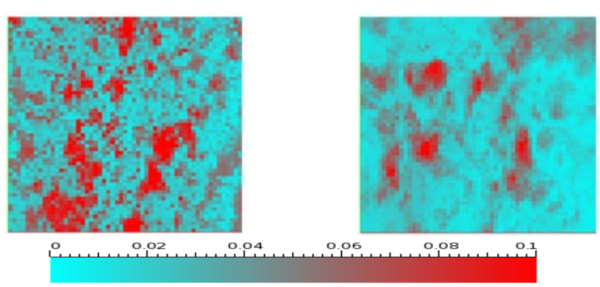

Figure 10: Average porosity deviation (cell by cell the difference between porosity in the initial and final model) from the prior computed from all the realizations. Left: grid-block approach. Right: multi-scale approach.

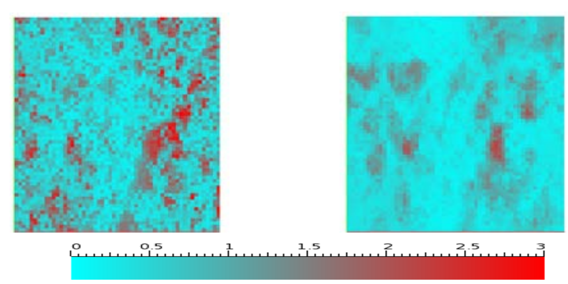

Figure 12: Average log-permeability deviation from the prior computed from all the realizations. Left: grid-block approach. Right: multi-scale approach.