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Distinguishing Signal from Noise in History Matching - Analysis of Ensemble Collapse on a Synthetic Data Set

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SUMMARY

Underestimation of posterior parameter uncertainty is one of the main problems encountered when doing history matching using ensemble based methods. In history matching results with the partial or full ensembles collapse, it is very hard to distinguish updates due to spurious correlation with noise in the data from the actual updates attributed to information in the data.
History matching of porosity and permeability based on well production data using the ensemble smoother with multiple data assimilation has been performed on a synthetic data set. The presence of ensemble collapse has been evaluated by different means: by looking at the stability of the update based on the starting ensemble, by adding dummy parameters to the update which do not affect the forward model, and by examining how well the data set used to generate the production data matches the posterior distributions of the parameters.
Ensemble collapse can be avoided by increasing the number of ensembles. This is however a prohibitively expensive strategy for cases with a large number of history data. Localization methods have been proposed in the literature as a way to increase the ensemble spread and hence avoid collapse, by for example limiting the analysis update to regions of influence of the data, while at the same time keeping the number of ensembles low.
A local analysis was performed to reduce the problems related to ensemble collapse. The results from the localized history matching produce a posterior distribution that better matches the original data set. Since our test data set is synthetic, we may perform measures of posterior uncertainty estimation by comparing with the true solution, with and without localization.

Introduction

When doing ensemble based history matching, the individual realizations in the ensemble are updated in such a manner that they match a set of observation points, for example well production profiles, 4D seismic data or well test results. The goal of the history matching is to gain additional insight about the set of parameters that cannot be directly measured, but can be used as input to a forward model to generate synthetic observations which can be compared with the actual observations.

The initial ensemble of realizations represents the prior distribution of the parameters, which will be updated by the history matching algorithm. The resulting ensemble of realizations represents the posterior distribution for the same parameters, i.e. an updated distribution where information from the observations is taken into account. Information attributed to the observations would then be visible as changes between the prior and posterior distributions, mainly as shift of the ensemble average and/or reduction in the posterior ensemble spread. It is also reasonable to expect changes in the correlations between the parameters, but this has not been considered in this study.

One major problem with doing ensemble based history matching is artificial updates of the distribution of the parameters which cannot be attributed to information from the observations. The presence of such artificial updates makes it very hard to determine whether the update of a single parameter can be attributed to information from the observations. Artificial updates are very easily introduced and may be a result both from limitations in the algorithms used for the history matching and spurious correlations between the updates of the parameters and the corresponding forward-modelled observations. In extreme cases, all the realizations in the final ensemble are virtually identical, giving rise to the term ensemble collapse. In this paper we broaden this term to encompass any significant update of the parameters in the ensemble that cannot be attributed to information derived from the observations.

The traditional way to reduce or eliminate the problem with ensemble collapse is to increase the ensemble size. However, this will lead to a big increase in the computing time needed to run the forward models. Localization has been proposed as a way of reducing the problem with ensemble collapse, effectively reducing the number of data points used when updating a single parameter value.

In this paper we first discuss the theory of ensemble collapse. A modest ensemble collapse is demonstrated when history matching a permeability field for a synthetic case. We base our analysis upon a dummy parameter (a parameter that is not included in the forward model) and inspection of the posterior ensemble variance. The latter is possible since the true parameter fields giving rise to the observations are known. The results are then compared to the results from a history matching experiment using a simple localization setup.

The experiments in this note use the ES-MDA, Ensemble Smoother with Multiple Data Assimilation, as implemented in ERT – Ensemble reservoir toolkit (ERT, 2016). Using this scheme, the ensemble smoother is run iteratively with different predefined weights for the observation uncertainty at each iteration. This scheme has shown good results for history matching (Emerick & Reynolds, 2013).

Theory

An ensemble collapse can be defined as an underestimation of the variance of the posterior ensemble. The collapse of the ensemble becomes apparent in real field situations where we cannot afford running a large number of ensembles. One usually identifies this problem by observing that the productions responses are very close (or collapse) into one response.

We review next some of the theory behind this feature. In the following, we denote by M the number of observations and N the number of ensembles. The analysis step A^a of the Ensemble Smoother is basically a linear combination of the forecast ensemble A:

$$A^a = A(I + S^T C^{-1} D') = AX,$$

where the matrix C (appearing in the so-called Kalman gain $K = A' S^T C^{-1}$) is defined as:

$$C = SS^T + EE^T.$$

Here S is a $M \times N$ matrix constructed from the forward ensemble of measurements, E is the ensemble of measurement perturbations, of size $M \times N$, and D is the ensemble of innovations or differences between the perturbed data and forward simulated data; see (Evensen, 2009). The matrix C, of size $M \times M$, can be seen as a mapping within the observation space, via the ensemble space. If $N < M$, this mapping has a non-trivial null space and will be rank-deficient. Therefore a pseudo-inverse needs to be computed in general. As shown in, among others, (Kepert, 2004), a straightforward calculation of the pseudo-inverse of C leads to the ensemble to collapse to a single member if $N \leq M/2 + 1$, and to partial collapse if $N \leq M$. An alternative pseudo-inverse computation proposed in (Evensen, 2003) and implemented in ERT, is to approximate the pseudo-inverse using a especial projection of the error matrix E. This approximation is known to prevent collapse. We mention also that the perturbation of the observations, though a crucial step in order to obtain a correct posterior covariance, may introduce sampling bias of the error covariance matrix (Kepert, 2004). The paper (Evensen, 2004) proposes improved sampling strategies to alleviate sampling biases.

As mentioned above, an important symptom of ensemble collapse is that the variance in the posterior ensemble is artificially low. One way to diagnose this is to add dummy parameters (which will be sampled independently of the actual parameters) to the workflow, that might get updated by the history matching algorithm, despite the fact that they have no influence on the forward model; see chapter 15 in (Evensen, 2009). An example of the use of the dummy parameter is given in the example.

Example

The Reek test case (Popa et al. 2014), shown in **Figure 1** (left), is a simple reservoir model with five production wells, named OP_1 - OP_5 and three injection wells named WI_1 - WI_3. The production results that we try to match are synthetic, meaning that we know the true reservoir that we want to match. This also means that all the realizations within the prior model will be reasonably close to the true reservoir, making it relatively easy to obtain a history match. An advantage of having the true solution is that it allows for deeper analysis of the results from the history matching. The true porosity and permeability are generated as stationary Gaussian random fields without any trends. The true permeability is in **Figure 1** (right).

Both porosity and permeability, together with fault multipliers were updated in the history matching experiments. In this paper we will focus on the permeability. The results from the history matching of the porosity show the same characteristics as the results for the permeability fields.

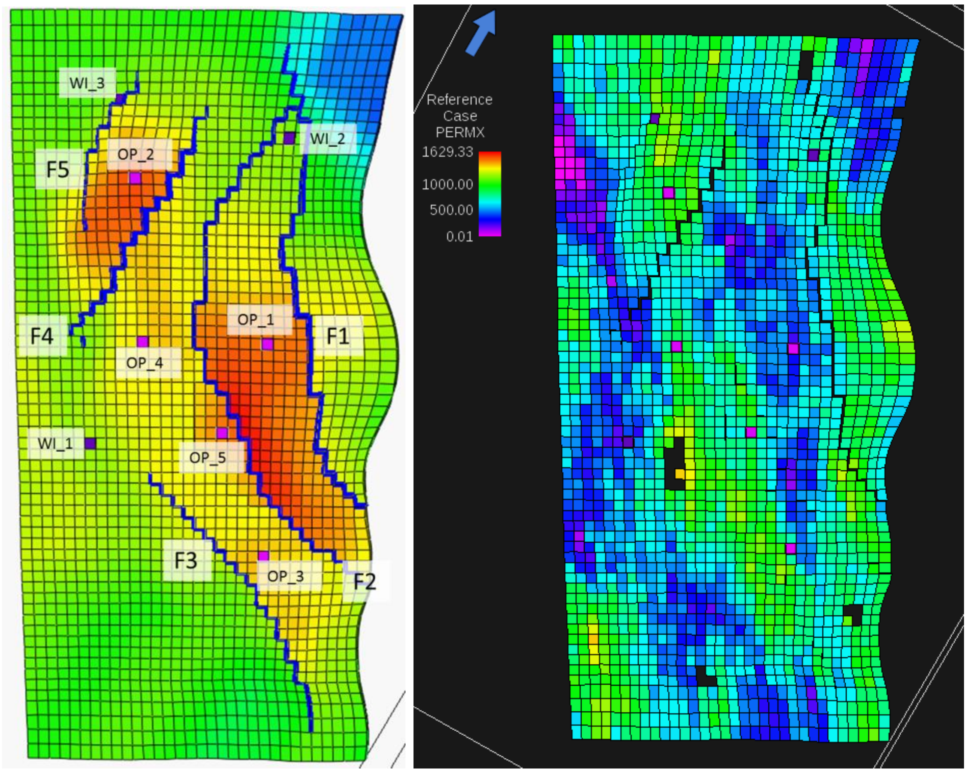

Figure 1 *Left: The Reek field with faults and wells shown. Cells coloured according to depth of the top surface. Right: The true permeability field used to generate the observations used in the history matching, shown at grid layer 3.*

Sensitivity analysis

The first step when running ERT is to test the sensitivity of the different parameters. This makes it possible to evaluate whether the initial ensemble of realizations contain the variability needed to honor the observations. The sensitivity to the parameters for the different observations also gives hints about how much information about the parameters that can be attributed to the observations, and thus how big of an update that we would expect to get from the history matching. The water cuts from wells OP_3 and OP_5 are not shown, since they are generally zero, both in the true solution and when doing the forward modeling of the ensemble realizations.

The results of the sensitivity study shown in **Figure 2** show that the production profiles from the forward modelled ensemble members cover the observed production values well, both in value and shape, and we should hence expect a good history match.

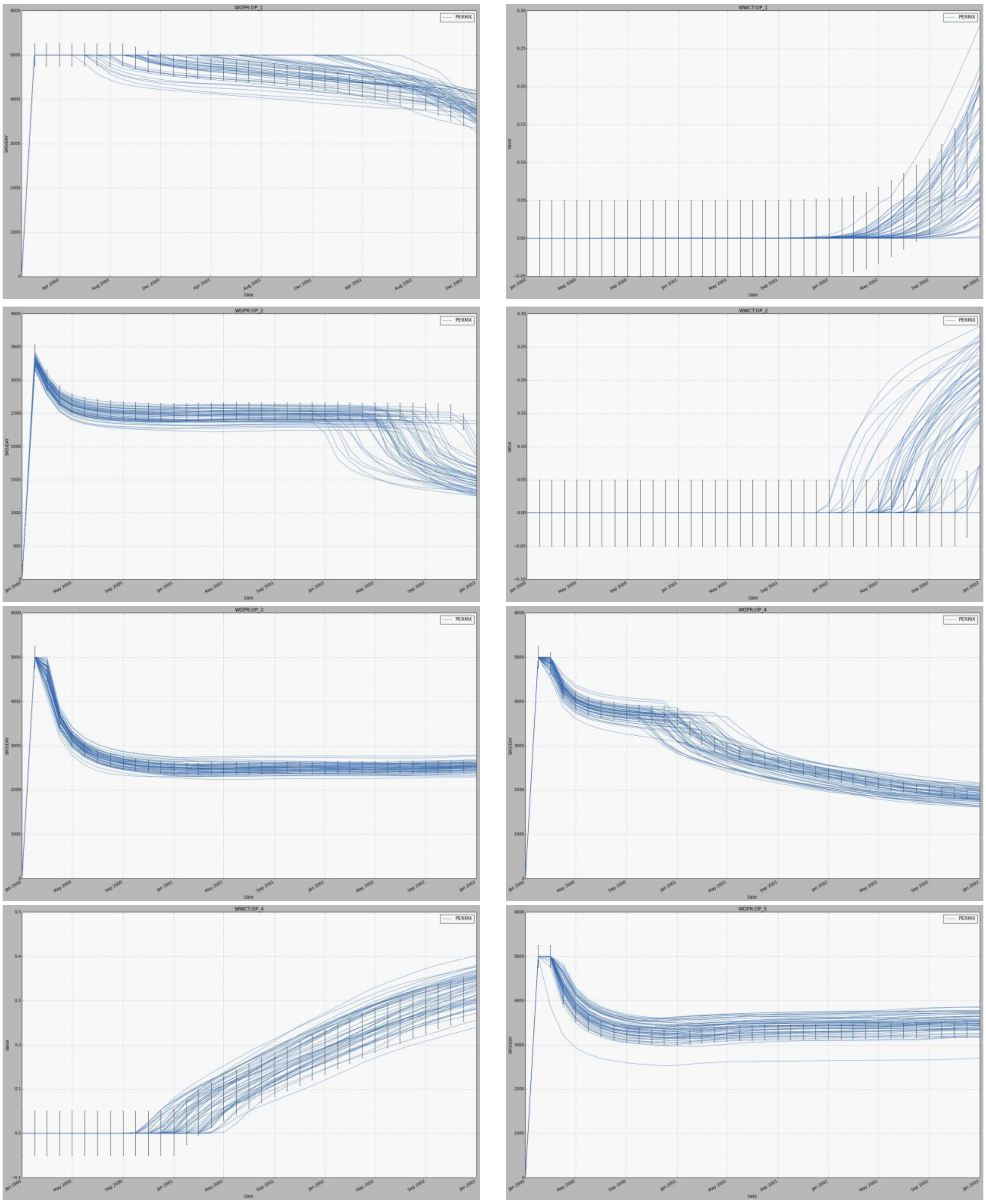

Figure 2 *The sensitivities on well production from modifying the grid cell permeabilities. From top left: oil production for OP_1, water cut for OP_1, oil production for OP_2, water cut for OP_2, oil production for OP_3, oil production for OP_4, water cut for OP_4 and oil production for OP_5.*

Results from running history matching

History matching was run on the Reek case, using the ensemble smoother with multiple data assimilation (ES-MDA) with four iterations with weights 0.6, 0.3, 0.1 and 0.1, and using an ensemble consisting of 50 realizations.

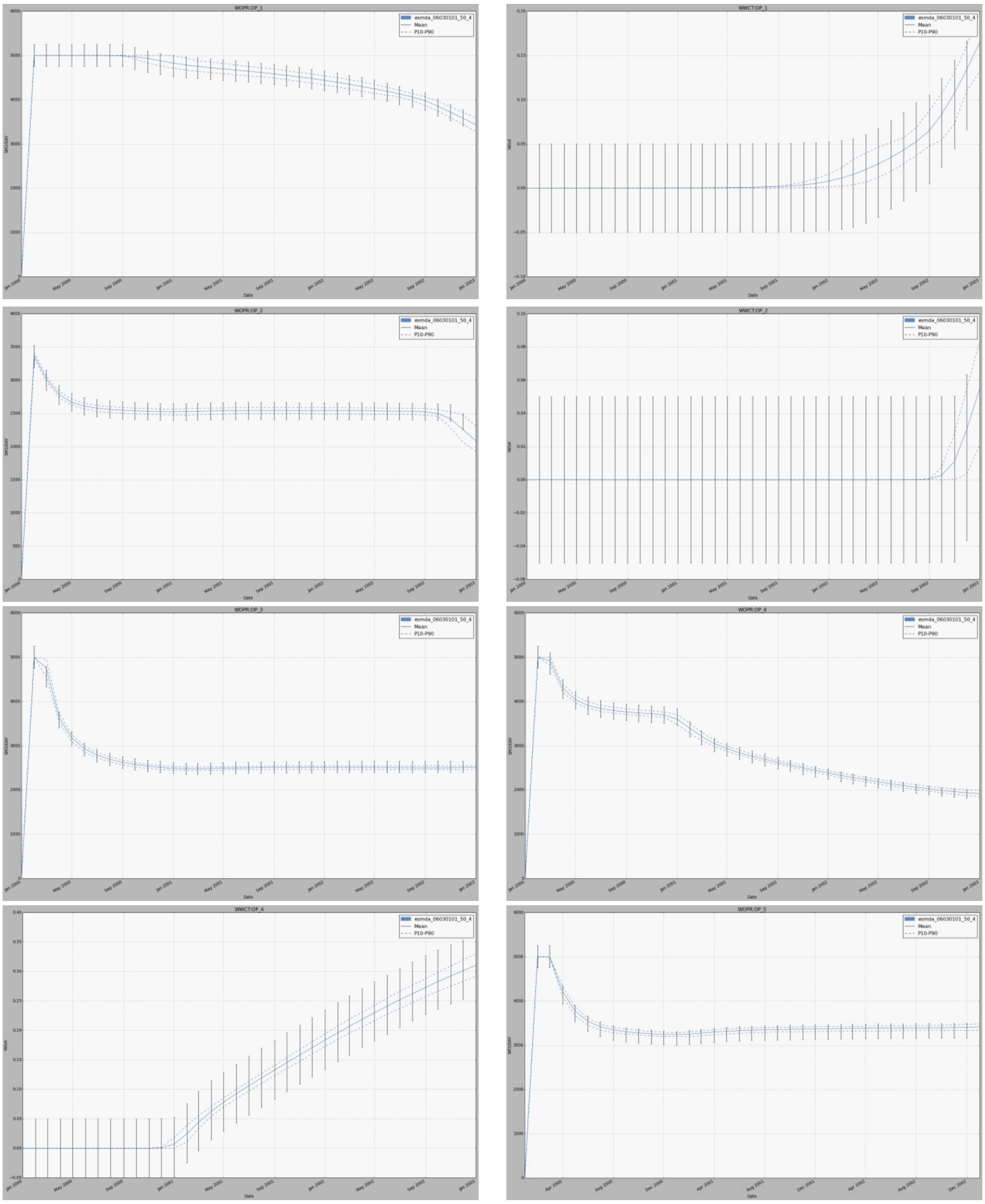

Figure 3 *History matched production profiles. The observations with uncertainty are given in black, and the posterior ensemble mean and spread are given in blue.*

As seen in **Figure 3** we get a very good match of the production profiles after history matching. Note that the posterior uncertainty is slightly smaller than the data uncertainty, but that there is no obvious evidence of a collapse.

The experiment was run with two dummy parameters not included in the forward model, but added to the analysis in the history matching. As shown in **Figure 4**, there is a slight update in these parameters.

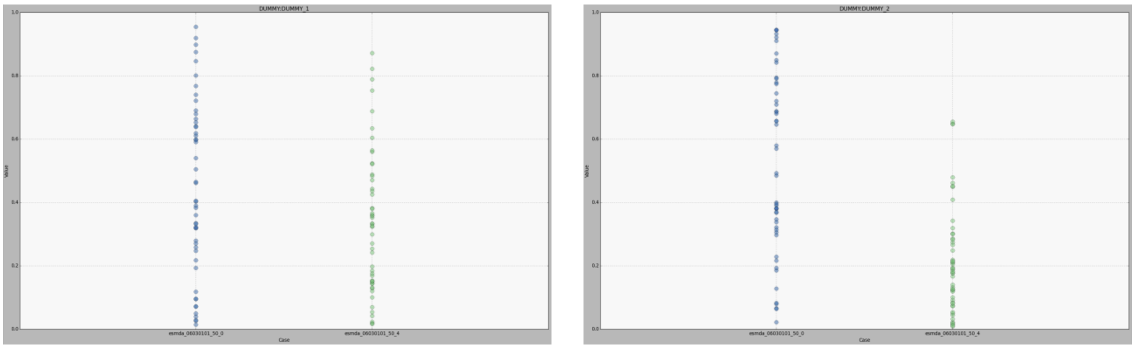

Figure 4 *Update of dummy parameters. Prior shown in blue, and updated posterior in green.*

Figure 5 and **Figure 6** show the update of the mean and standard deviation of the permeability of the realizations in the ensemble. Note that the prior average and standard deviation fields are almost constant as expected, since there were no trends used when making the realizations.

Some of the features from the "true case" seem to be captured in the a posteriori update, especially the low permeability and porosity area around OP_1, and the high permeability and porosity area around OP_2, however we get similar updates in areas in the corners were the permeabilities should have little influence on the well production. We also have updates that are contrary to the true case, cf. Figure 1.

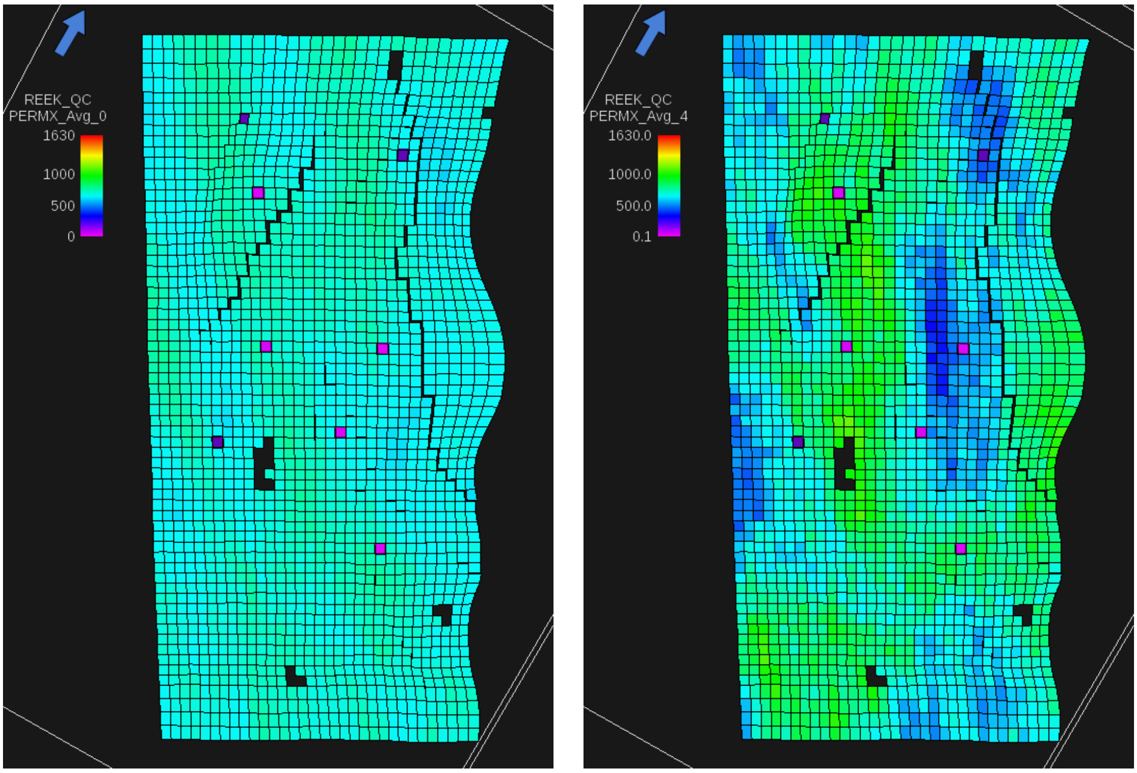

Figure 5 *Average permeability from the realizations in the prior ensemble (left) and the posterior ensemble (right) from layer 3.*

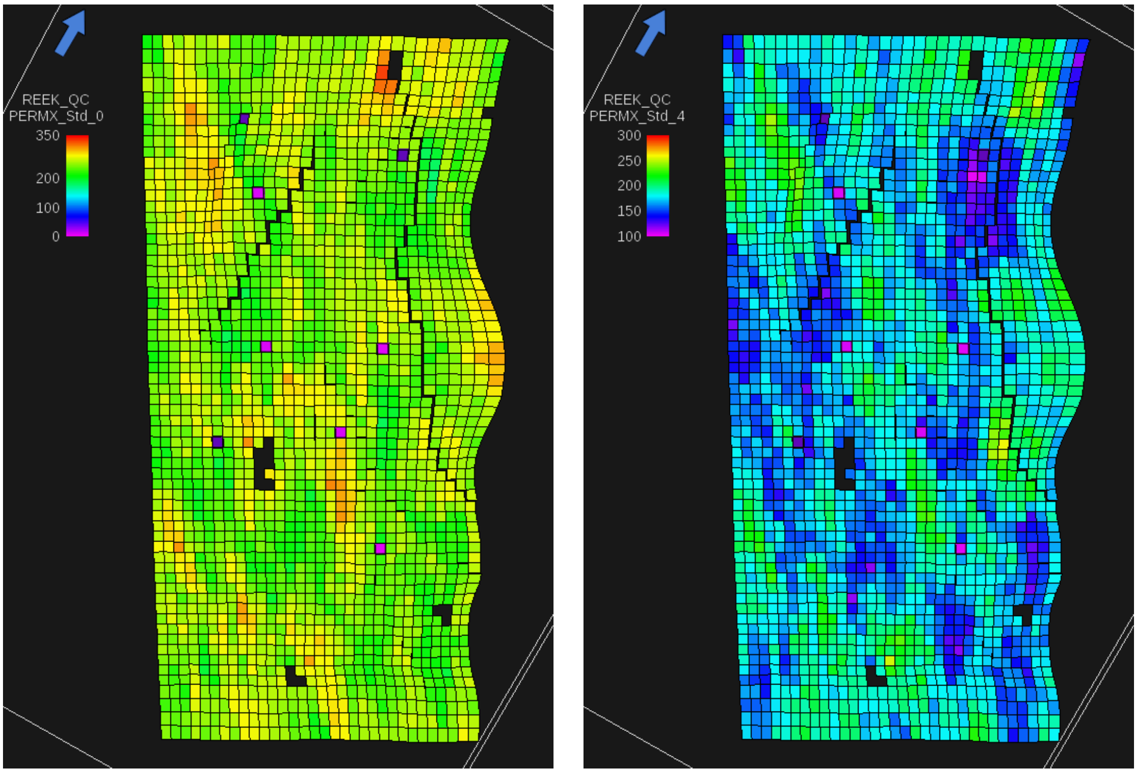

Figure 6 *Standard deviation for the permeability of the realizations in the prior ensemble (left) and the posterior ensemble (right) for layer 3. (Notice the slight difference in scale)*

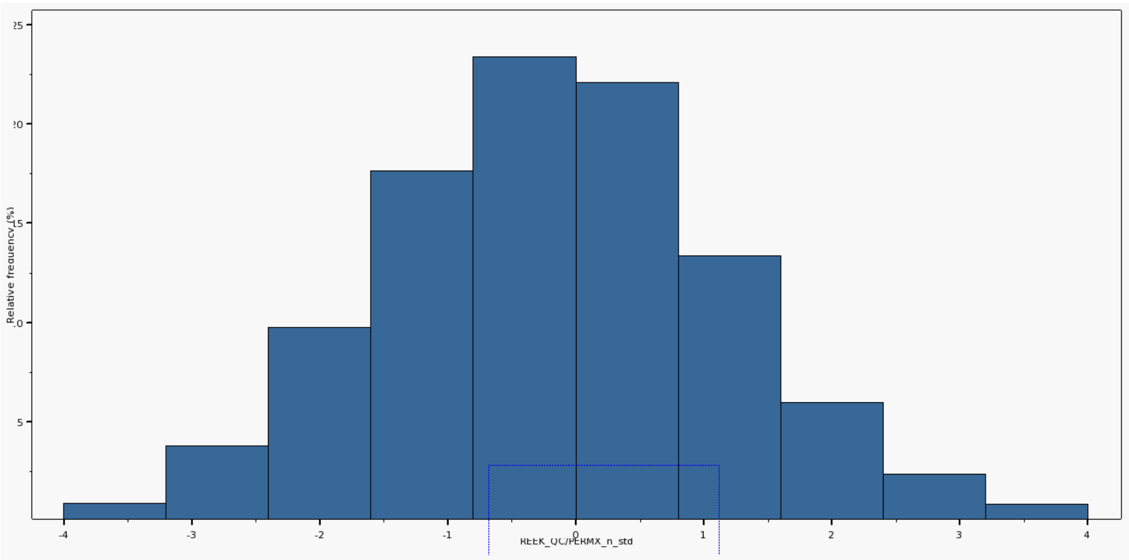

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Figure 7 *Histogram for true the permeability, standard distributed using the posterior distribution.*

From **Figure 6** we see that the a posteriori standard deviation is significantly reduced compared to the a priori standard deviation. The average standard deviation over the whole permeability field is 248 a priori, and 178 a posteriori, giving a factor of 1.39 between prior and posterior standard deviation. A similar underestimation of the standard deviation was reported in (Chen & Oliver, 2010).

Since we have the “true” fields, we can compare these to the predictions based on the history matching. If we denote the true permeability value k_{true}, and the estimated mean and standard deviation for the permeability $\bar{k}$ and s_k, we would expect the transformed permeability

$$\tilde{k} = \frac{k_{true} - \bar{k}}{s_k} \tag{1}$$

to be standard normal distributed *N(0,1),* if $\bar{k}$ and s_k are good estimates for the posterior distribution. **Figure 7** shows the histogram for this measure calculated for each cell in the grid. As observed there, we have a mean value that is slightly below zero. Further investigations are needed to examine whether this is just a coincidence, or if it is a consistent bias in the methodology. We also see that we get a standard deviation of 1.37, indicating that the posterior standard deviation is underestimated by a factor of 1.37. This is just slightly lower than the reduction in standard deviation seen in **Figure 6**.

This reduction in standard deviation is thus an indicator of a slight collapse in the history matching algorithm. Based on this we conclude that the updates in the field parameters are almost completely due to ensemble noise, and that it is very hard to extract any information from the results of the history matching experiment. This is also reasonable, given that the calculations of the pseudo-inverse done in the ensemble update indicate that the production profiles used correspond to only about 7 independent data points, and it is limited how much information these data can give for two parameter fields, each with 27755 cells, even if the fields are strongly spatially correlated.

History matching with localization

As a means to reduce the collapse, a simple localization scheme was attempted. In the localization setup used, the production data from each production well was used to only update grid cells with a distance less than 500 meters to this well. As a result of this, only 2550 grid cells out of a total of 27755 grid cells were updated.

As seen in **Figure 9**, even if we only update the porosity and permeability in relatively few grid cells, we get a very good history match for all the wells, except OP_1. We note that the spread is larger than in **Figure 3**, but for OP_2 - OP_5 the history matched production profiles are generally within the data uncertainty. Looking at the reservoir geometry and the updates from the non-localized experiments, we guess that including grid cells around the water injector well WI_2 in the localization setup for OP_1 could give a better match with the production profiles, but this has not been tested.

As seen in **Figure 4** there is virtually no update of the spread of the dummy parameters, suggesting that there is no significant ensemble collapse.

Figure 8 *Update of dummy parameters. Prior shown in blue, and updated posterior in green.*

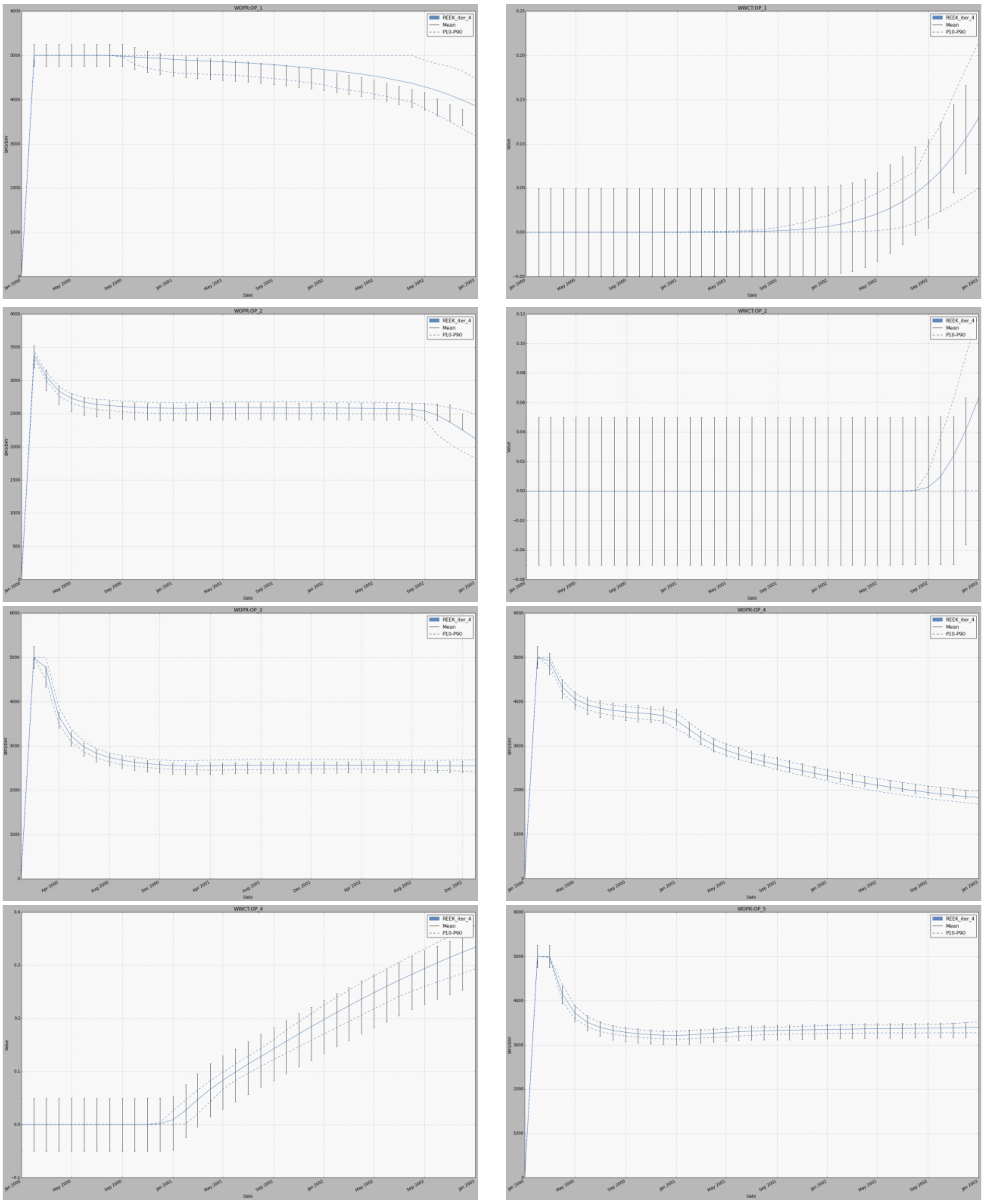

Figure 9 *Posterior production profiles for history-matching with localization.*

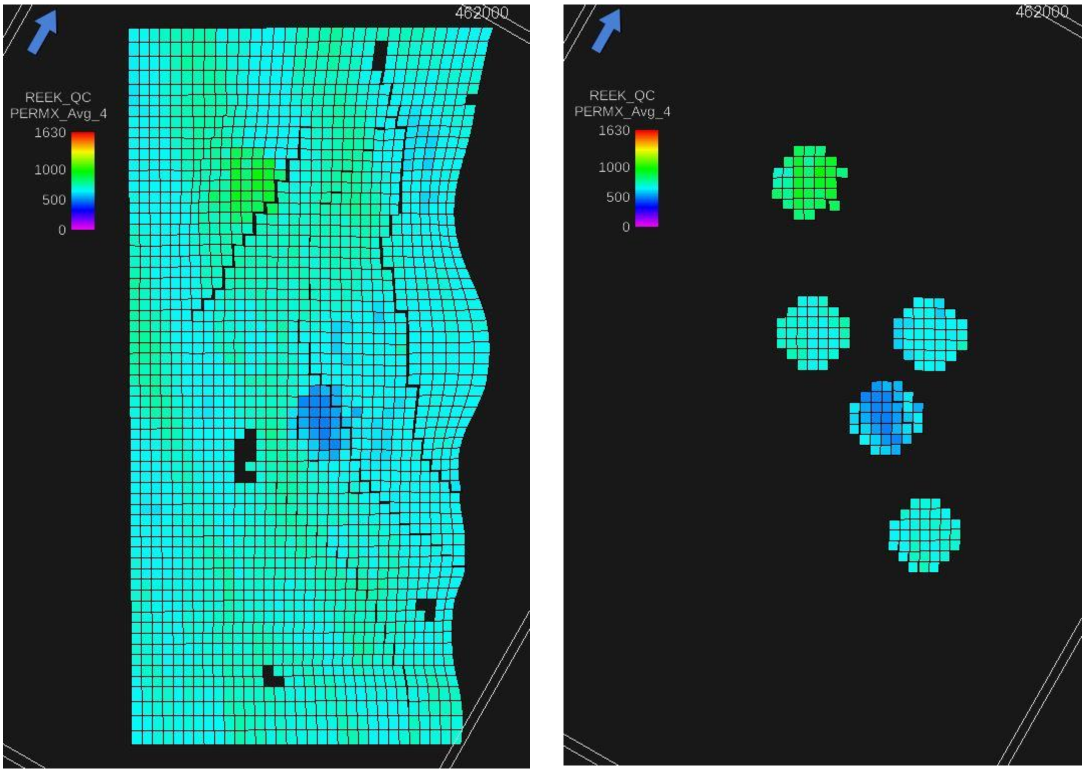

Figure 10 *Update of permeability for layer 3. To the left: the whole grid; to the right: just the localized areas.*

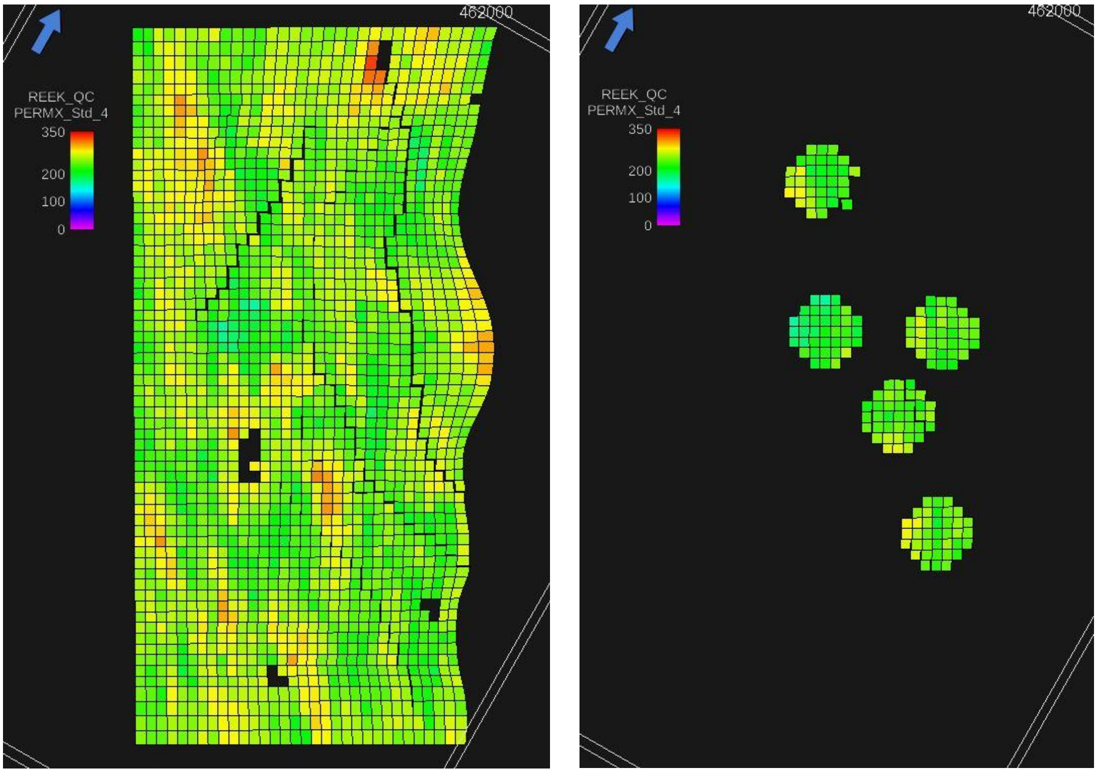

Figure 11 *Update of standard deviation for permeability for layer 3. To the left: the whole grid; to the right: just the localized areas.*

Figure 10 and **Figure 11** show the updated mean and standard deviation for the permeability field. The prior fields are still given in **Figure 5** and **Figure 6**, while the true case is given in **Figure 1**. We see that we in general get a much smaller update than in the non-localized case, and especially the standard deviation is virtually the same in the updated and non-updated areas as seen in **Figure 11**. When looking at the standard deviation values, the prior average 246, while the posterior average is 226.

We get some significant updates around OP_2 and OP_5. The update of OP_2 matches the true case quite well, but the match is less obvious for the other wells. One possible interpretation of the updates is that it tells something about how the average field values in a volume around the well, and may also contain information about the local trends.

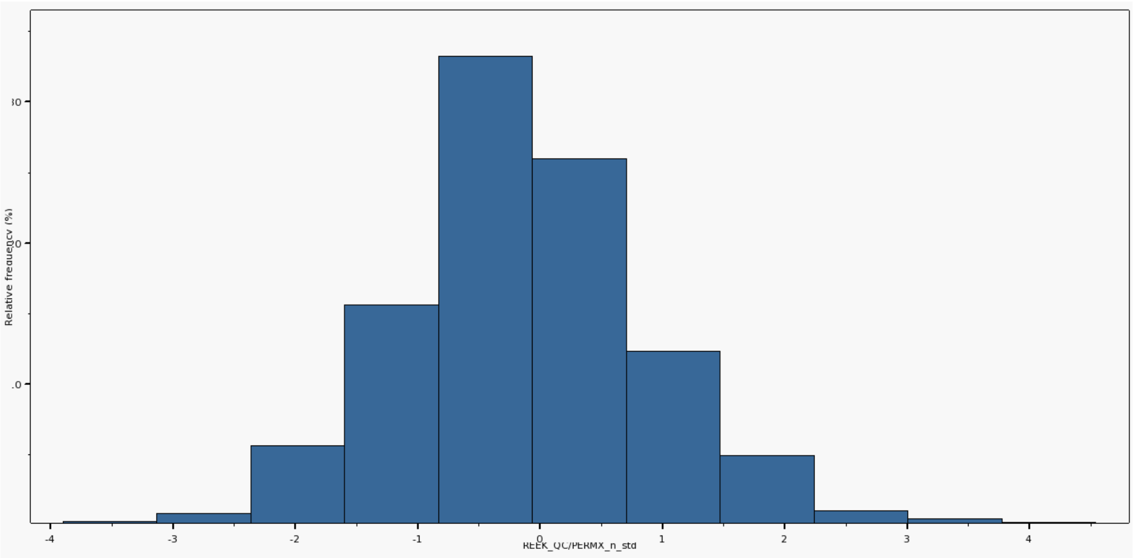

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Figure 12 *Histogram for the true permeability normalized using the posterior distribution.*

Figure 12 shows the histogram for the transformed true permeability as calculated from equation 1, calculated only for the grid cells that were updated during the history matching. We still have a slight bias, with a mean of -0.18, but the standard deviation is very close to 1 meaning that we have no collapse. This again means that the slight reduction in standard deviation observed above is a sign of actual information being added to the model by the history matching.

Conclusions

Care should be taken to distinguish between results just due to spurious effects, and results that contain information derived from the actual observations when using results from an automated history matching workflow. Using an ensemble based approach makes it possible to estimate posterior distributions, making it possible to evaluate whether the observations contain information about a given parameter or not. Ensemble collapse can pollute these results, by giving artificially updated posterior distributions for the parameters. It is therefore very important to QC the obtained results in this regard.

Localization can be a way of reducing the problem with ensemble collapse without needing to run too many realizations. However, care has to be taken to ensure that the problem with ensemble collapse is minimized, while at the same time the localization setup is such that the desired information about the reservoir can be derived from the history matching results.

Acknowledgements

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