

## Influence of Localization Technique on the Kalman Gain in a History Matching Process

[Ricardo Vasconcellos Soares](#)

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### Introduction

The objective of this text is to show an application of an ensemble based methodology derived from Kalman Filter (KF) in conjunction with localization technique to verify the main applications and limitations of these methods (Soares, 2017).

Ensemble based methods derived from KF are becoming interesting for O&G industry, once they can deal with a great amount of uncertain data and can also generate good data matches with relatively small number of flow simulation when compared with other methods, such as Randomized Maximum Likelihood (RML) and Markov Chain Monte Carlo (MCMC). Among them, it is possible to highlight the Ensemble Smoother with Multiple Data Assimilation (ES-MDA), proposed by Emerick and Reynolds (2013), that became an attractive method, once it assimilates data in one single update and it is an iterative method. Consequently, it generates good data matches in a reasonable number of flow simulations, even when compared with other ensemble based methods derived from KF.

The motivation to this work was the possible underestimation of the uncertainties generated by the ES-MDA (as a consequence it can fail to represent some possible answers of the problem, which may include the real one) as reported by Morosov and Schiozer (2016).

Additionally, they also may generate spurious correlation between input and output of the reservoir models; to deal with these issues, the use of the localization technique is recommended in the literature.

One of the most used types of localization is the distance dependent localization, where an influence region for each well is defined, and the data from each well is used to update the uncertain variables (porosity and permeability, for instance) only in these defined regions. The most important aspect of this technique is regarding the definition of the influence area.

### Methodology

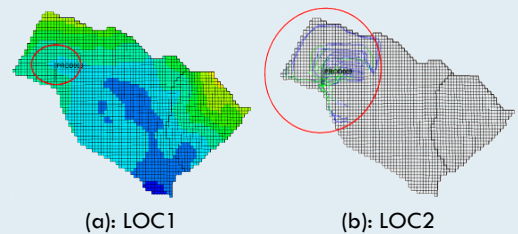
In this work, we applied the ES-MDA for the same model under three different approaches.

The first approach, called as STD, uses the ES-MDA method without the localization technique. The second one (LOC1) involves the utilization of the distance dependent localization technique, and the influence region are defined according to the influence area of each producer-injector well pair, generating small influence areas. The third approach (LOC2) uses bigger influence regions, defined according to the streamlines of a model that represents the average of the prior models. Figure 1 illustrates the difference between influence regions for LOC1 and LOC2 for well PROD009.

From these approaches, the methodology is complemented by the following steps:

- 1) Data match analysis through a multi-objective function (NQDS).
- 2) Analysis of the variability of the models and the uncertainties responses.
- 3) Selection of accepted models (filter) according to the multi-objective function defined in Step 1.
- 4) Production forecast of the filtered models.
- 5) Analysis of key parameters of the ES-MDA meth-

od, such as number of models ( $N_e$ ) and iterations ( $N_i$ ).



**Figure 1:** Influence regions for well PROD009: LOC1 (a); LOC2 (b).

### Application

The methodology was applied in the benchmark case based on data from Namorado field, UNISIM-I-H (<https://www.unisim.cepetro.unicamp.br/benchmarks>).

Regarding the application of ES-MDA, initially we defined the number of models as 500 and the number of iterations as 4. It is important to say that at the end of the step 4 of the methodology, it was possible to define the best approach among the three tested (STD, LOC1 and LOC2) and, after that,  $N_e$  and  $N_i$  were analyzed separately.

### Results

The main variable limiting match quality was the water rate (produced and injected) for all three approaches. In addition, when comparing them, we observed that LOC1 presented models with the worst data match quality.

STD showed a great reduction of variability of the final ensemble, achieving a value of Sum Normalized Variance (SNV) of about 23%, while for LOC1 and LOC2, SNV achieved 90% and 74%, respectively. It is important to point out that scalar uncertainties, which are represented by a single value for the whole model or a section of it (water relative permeability, for example), presented a very strong reduction of their variability. While petrophysical uncertainties, such as porosity and permeability, had greater variability for the approaches with localization.

Furthermore, a plot of the mean image of the 500 models of  $\ln(k_x)$  showed that STD case generated images with spurious correlation, where there is no physical explanation for some updates in the model, as shown by Figure 2a, and this did not occur for the other approaches. However, once we defined small influence regions for LOC1, some updates were too restricted (Figure 2b). Finally, using bigger influence areas (LOC2), we achieved a smoother image (Figure 2c).

Due to the poor quality of data match, only 6.2% of the 500 models (final ensemble) were filtered for LOC1, showing that the influence regions defined did not represent well the real influence areas. Additionally, for STD and LOC2 approximately 66% and 83% were filtered, respectively.

Finally, when forecasting the production of the filtered models and plotting a cumulative probability curve at the end of the forecast time, the only approach that encompassed the reference response for oil cumulative production ( $N_p$ ) was LOC2 (Figure 3a). However, all approaches, tended to overestimate  $N_p$ . For  $W_p$  (Figure 3b), all approaches en-

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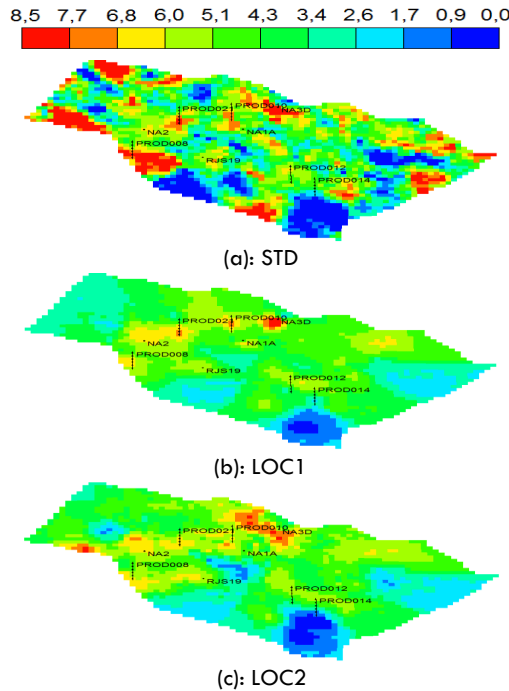


Figure 2: Posterior distribution of mean of  $\ln(kx)$ : STD (a); LOC1 (b); LOC2 (c).

compassed the reference response, and LOC2 can be highlighted, once it achieved a very symmetrical response in relation to the reference answer.

With this information, we selected LOC2 as our best approach, once it generated better data matches, avoided spurious correlation, generated smoother images and encompassed the response of the reference model. Thus, from this approach, we analyzed Ne and Ni.

Firstly, Ne was changed to 250 and 100 and we observed that it has a great influence in the reduction of the variability, especially for scalar uncertainties. For the case with 100 models, for example, the values of maximum water relative permeability practically collapsed in one single value. Also, due to the limited amount of data, Ne=100 generated images with spurious correlation, as also observed for STD. In summary, the posterior distribution generated for all three cases were different, resulting in distinct forecast response, where the only one capable of encompassing the reference answer was the case with 500 models.

From LOC2 with 500 models, we varied the number of iterations to 2 and 6. Its variation had a great impact in the data match, once the quality of data match is directly proportional to Ni. One very important aspect noticed was the fact that with the increase in Ni, values of SNV and scalar uncertainties were converging to similar results, which is an indicative that the method converged to more representative responses of the reference model. In fact, the cumulative probability curve for Np at the end of the forecast production was more symmetrical in relation to the reference response when we used 6 iterations (Figure 3a).

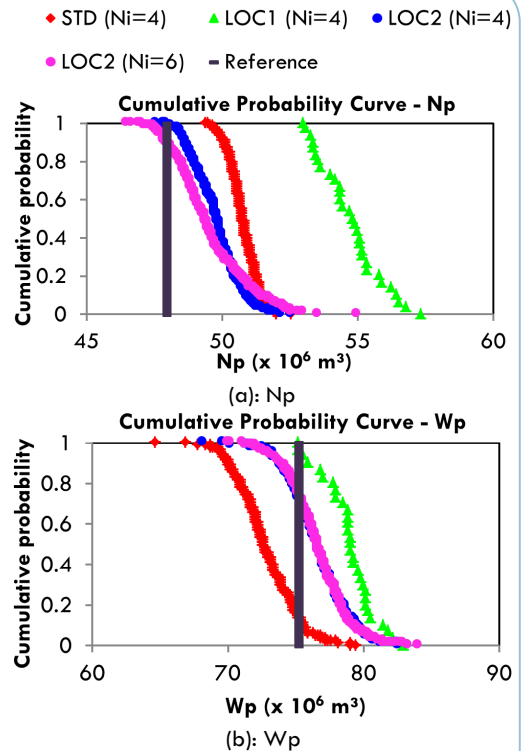


Figure 3: Cumulative probability curve at the end of the forecast time: Np (a); Wp (b).

**Conclusions**

ES-MDA is a robust method capable of dealing with a great number of data and generating good history matching but may need improvements to avoid excessive uncertainty reduction. We have shown that without the localization technique there is a great reduction of the variability and presence of spurious correlation. Moreover, we have shown that localization helped to increase the variability and generate models without spurious correlation, but its use has to be carefully analyzed, once proper definition of influence regions is crucial for the effectiveness of the method. Finally, other parameters, such as Ne and Ni, also had a great impact on the final response and they should be taken into account before start the process.

**References**

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