IOP Conference Series: Materials Science and Engineering

PAPER • **OPEN ACCESS**

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To cite this article: R Guliev and A Zolotukhin 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **700** 012054

IOP Conf. Series: Materials Science and Engineering **700** (2019) 012054 doi:10.1088/1757-899X/700/1/012054

Field development optimization of waterflooding process using data assimilation methods

R Guliev[1*] and A Zolotukhin[1, 2, 3]

[1] Northern (Arctic) Federal University named after M.V. Lomonosov, Severnaya Dvina Emb. 17, 163002, Arkhangelsk, Russia
[2] Gubkin Russian State University of Oil and Gas (National Research University), Leninsky prospect 65, 119991, Moscow, Russia
[3] The University of Stavanger, P.O. Box 8600 Forus N-4036 Stavanger, Norway

* Corresponding author: ramilguliev1@gmail.com

Abstract. The application of data assimilation methods for field development optimization has been the subject of intense investigation during the past 10 years. Lately has seen remarkable progress in the ability of data assimilation approach in reservoir characterization and based on this, improvements of field development optimization. In this review paper, we have summarized key achievements in field development optimization of waterflooding process with data assimilation approach and review many of the achievements of the past time, including developments in the field of search for modifications of Ensemble Kalman Filter (EnKF) and Ensemble Smoothers (ES). An attempt has been made to discuss different data assimilation methods and to identify possible limitations of each. Current challenges and future research opportunities for improved data assimilation methods for field development optimization of waterflooding process are also discussed.

1. Introduction

Different studies have shown that model-based dynamic optimization of the waterflooding process improves the economic life-cycle performance of oil fields, see e.g., [1, 2]. One of the main challenges in this optimization is the high levels of uncertainty increasing from the modeling process of waterflooding. As a result, the potential advantages of dynamic optimization are not fully realized and the optimized objective value is not obtained.

Different approaches of waterflooding optimization under uncertainty can be broadly divided into two types. In the first type, also known as open-loop schemes, a decision maker selects a strategy without knowing the exact values taken by the uncertain parameters, and the exact values are assumed to belong to an uncertainty space. In the second type, also known as closed-loop (Closed-Loop Reservoir Management (CLRM)), the strategy is allowed to update/adjust to information that is revealed over time. This article discusses only CLRM type of waterflooding optimization.

Uncertainty quantification of the uncertainty space is one of the essential steps in CLRM. A general practice of quantifying uncertainty in waterflooding optimization in CLRM is implementation of data assimilation methods such as Ensemble Kalman Filtering (EnKF), Ensemble Kalman Smoothing (EnKS), Particle Filtering, variational approaches etc. The purpose of this work is to overview different types of data assimilation methods in task of closed-loop reservoir management and identify limitations of them.

The article is structured as follows. Section 2 discusses the basics of closed-loop reservoir management optimization. In Section 3, is discussed different data assimilation methods followed by conclusions in section 4 with discussion of current challenges and future research opportunities for improved data assimilation methods for field development optimization of waterflooding process.

2. Closed-Loop Reservoir Management

Closed-loop reservoir management (CLRM) is a cycle of production optimization and data assimilation (see Fig. 1). Aim of cycle of optimization at finding maximum of value. e.g. financial measure (Net Present Value (NPV)), over the producing period of the reservoir by optimizing the production parameters. For more information about CLRM see, e.g., [3], [4], and [5].

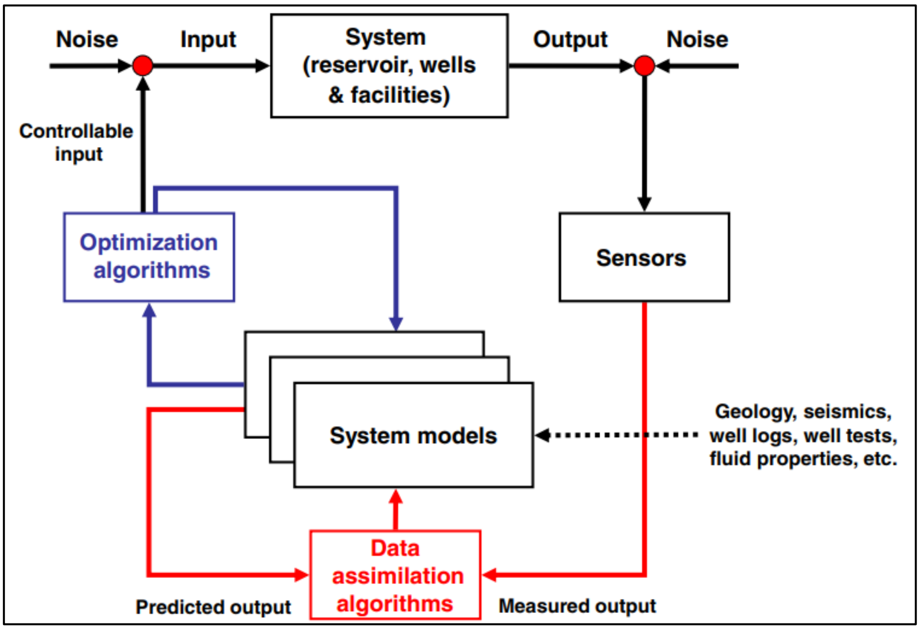

Figure 1. Closed-loop reservoir management (Source: [3])

NPV can be represented as:

$$J = \sum_{k=1}^{K} \left[\frac{r_o \cdot q_{o,k} - r_w \cdot q_{w,k} - r_{inj,k} \cdot q_{inj,k}}{(1+b)^{\frac{t_k}{\tau_t}}} \cdot \Delta t_k \right], \tag{1}$$

where r_o , r_w and r_{inj} are the oil price, the water production cost and the water injection cost, respectively. K represents the production period and Δt_k is the time interval of time step k . b is the discount rate for a certain time τ_t . $q_{o,k}$, $q_{w,k}$ and $q_{inj,k}$ is the cumulative production of oil, water and injected water at time step k .

Uncertainty is one of the main aspects of the model-based optimization of the waterflooding process. To quantify the uncertainty space Θ in waterflooding optimization, usually use an ensemble of uncertain model realizations. This set of ensemble-based uncertainty can be used with various schemes. One of the robust approaches is to maximize the average of the NPV objective over the model uncertainty ensemble [6].

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Robust optimization can be formulated as:

$$J_O = \frac{1}{N_e}\sum_{k=1}^{N} J_i(\mathbf{u},\boldsymbol{\theta}_\mathbf{i}), \tag{2}$$

where J_i is the NPV objective and $\mathbf{u}$ is the input decision variable, $\boldsymbol{\theta}_\mathbf{i}$ is a vector of uncertain model parameters.

Now we can formulate the optimization problem as finding a vector $\mathbf{u}$ including the set of the control parameters over the producing period of the reservoir. It should be noted, that although the optimization is based on N_e models, only a single strategy $\mathbf{u}$ is obtained. Typical elements of $\mathbf{u}$ are settings of well head pressures, water injection rates, valve openings, etc. Sometimes the problem is very nonlinear and nonconvex, i.e. it has multiple local maxima.

3. Data Assimilation

As we mention before, uncertainty quantification is one of the essential steps in closed-loop reservoir management. One of the types of uncertainty is ambiguity of geological properties. A prior distribution of the geological properties can be generated using various geostatistical techniques. Also, various measurements (y) suitable to unknown model parameters (θ) are available from surface and sensors. From a probabilistic point of view, Bayesian inference provides a good platform to compute the posterior probability density function (PDF) [7]:

$$p(\theta \mid y) = \frac{p(y \mid \theta) p_{pr}(\theta)}{p(y)}, \tag{3}$$

where $p_{pr}(\theta)$ is the prior distribution, $p(y)$ is the density function of the measurements and $p(y \mid \theta)$ is the likelihood function for obtaining y given the model parameters θ. In our CLMR case, prior and posterior model parameters θ represented prior and posterior ensembles, respectively.
The main assumption in data assimilation is reducing uncertainty of the model parameters leads to an improved forecast capacity of the models, which, in turn, leads to improved decisions. In our CLRM case, decisions take the form of control vectors $\mathbf{u}$, aimed at finding maximum of the objective function J_O.

3.1 Ensemble Kalman Filter

Recently, the Ensemble Kalman Filter has gained popularity as a data assimilation method. EnKF is based on the Kalman filter [8], but simple Kalman filter can't be implemented for data assimilation of large models, especially with non-linear components.

Below shown the algorithm of EnKF implementation:

1. Generate N_e samples $\theta_i^{a,j}$ and $J_i^{a,j}$, $j = 1..N_e$ from the prior distribution of $p_{pr}(\theta)$ and the initial distribution of J.

2. For $i = 1..N_e$,

2.1 Generate N_e independent samples of J_i by integrating each sample from t_{i-1} to t_i using the forward model. In J_i, the most updated value for $p_{pr}(\theta)$, is applied. That is, for $j = 1..N_e$:

$$J_i^{f,j} = \begin{Bmatrix} J_i^{f,j} \\ \theta_i^{f,j} \\ g_i^{f,j} \end{Bmatrix} = \begin{Bmatrix} J_{i-1}^{f,j} \\ F(J_{i-1}^{f,j}, \theta_{i-1}^{f,j}) \\ g(J_{i-1}^{f,j}, \theta_{i-1}^{f,j}) \end{Bmatrix}, \tag{4}$$

where F_i denotes the forward integration of equations of dynamic model from step of time $i-1$ to i and g_i denotes set of measurements. $\theta_i^{f,j}$ represents a sample from prior distribution). Superscript a denotes posterior solution from previous step.

2.2 Use Monte-Carlo approach for estimation of the first- and second-order moments from prior, using ensemble mean of matrix $\mathbf{Y}_i$ with each ensemble members

$$\bar{\mathbf{Y}}_i = \{\bar{J}_i^1..\bar{J}_i^{N_e}\} \tag{5}$$

and using covariance matrix:

$$\mathbf{C}_{J_i} = \frac{\Delta\mathbf{Y}_i \Delta\mathbf{Y}_i^T}{N_e - 1} \tag{6}$$

2.3 Generate N_e independent samples from the measurements distribution:

$$y_i^j = y_{obs,i} + \varepsilon_i^{d,j}, j = 1..N_e \tag{7}$$

2.4 Update each ensemble member using the traditional Kalman filter update:

$$J_i^a = J_i^f + \mathbf{K}_i(y_{obs,\mathrm{i}} - \mathbf{H}J_i^f) \tag{8}$$

$$\mathbf{K}_i = \mathbf{C}_{J_i^f}\mathbf{H}^T(\mathbf{H}\mathbf{C}_{J_i^f}\mathbf{H}^T + \mathbf{C}_{y_i})^{-1}, \tag{9}$$

$$J_i^{a,j} = J_i^{f,j} + \mathbf{C}_{J_i^f}\mathbf{H}^T(\mathbf{H}_i\mathbf{C}_{J_i^f}\mathbf{H}^T + \mathbf{C}_{y_i})^{-1}, j = 1..N_e \tag{10}$$

where ε_i denotes measurements error, $\mathbf{K}$ denotes Kalman gain matrix, $\mathbf{H}$ denotes relationship between measurements and states.

Examples of implementation of EnKF: Consider a several examples of implementation EnKF: assimilating data of production history, assimilating seismic data and implementation of EnKF in CLRM.

Haugen et al. [9] implemented EnKF to improve history matching from production data from North Sea field. They used large nonlinear reservoir model. This work has been showed that we can improve model parameters (permeability and porosity) by assimilating production data such as bottom hole pressure and production rates of oil, gas, and water. It has been demonstrated that by using the EnKF, a better history-matched model could be obtained. In work [10] used to assimilation porosity fields used to model an oil reservoir with almost three years of production. Work was confirmed the possibility to use EnKF for history matching of real reservoir models.

Second group of works with implementation of EnKF considers works related with implementation of EnKF for data assimilation of seismic data. Skjervheim et al. [11] studied EnKF inversion scheme to assimilate interpreted seismic data into reservoir simulation models for both a 2D model and a real field and got ambiguous results.

Third and most interesting for us case is implementation of EnKF in CLMR. Chen et al. [12] implemented EnKF in closed-loop reservoir management for improvement waterflooding process. EnKF was in couple with optimization algorithm – EnOpt. The aim of this work was to maximize NPV through management of control devices.

The applicability of the EnOpt algorithm and the ensemble-based CLRM is assessed through the use of two examples. In the first example, the control devices are optimized by the EnOpt based on a known reservoir model. The results showed the ability of the EnOpt to improve reservoir management in the presence of complex features. The ensemble-based CLRM is demonstrated in the second example and the results are compared with other alternative control strategies. A good estimate of the permeability field (Fig. 2), which captured the features of the reference field. The net present value of the field is significantly increased by the CLRM.

3.2 Ensemble Smoothers

The Kalman filter is a recursive filter with the Markov property – it's estimate at step k is based only on the estimate from step $k-1$ and the measurement at step k. But this means that the estimate from step $k-1$ is based on step $k-2$, and so on back to the first epoch. Hence, the estimate at step k depends on all of the previous measurements, though to varying degrees. $k-1$ has the most influence, $k-2$ has the next most, and so on.

Smoothing filters incorporate future measurements into the estimate for step k The measurement from $k+1$ will have the most effect, $k+2$ will have less effect, $k+3$ less yet, and so on.

There are different types of ensemble smoothers: Fixed-Interval Smoothing, Fixed-Lag Smoothing, Fixed-Point Smoothing and more algorithms of smoothing and this is a topic for discussion of future research of ensemble smoothers.

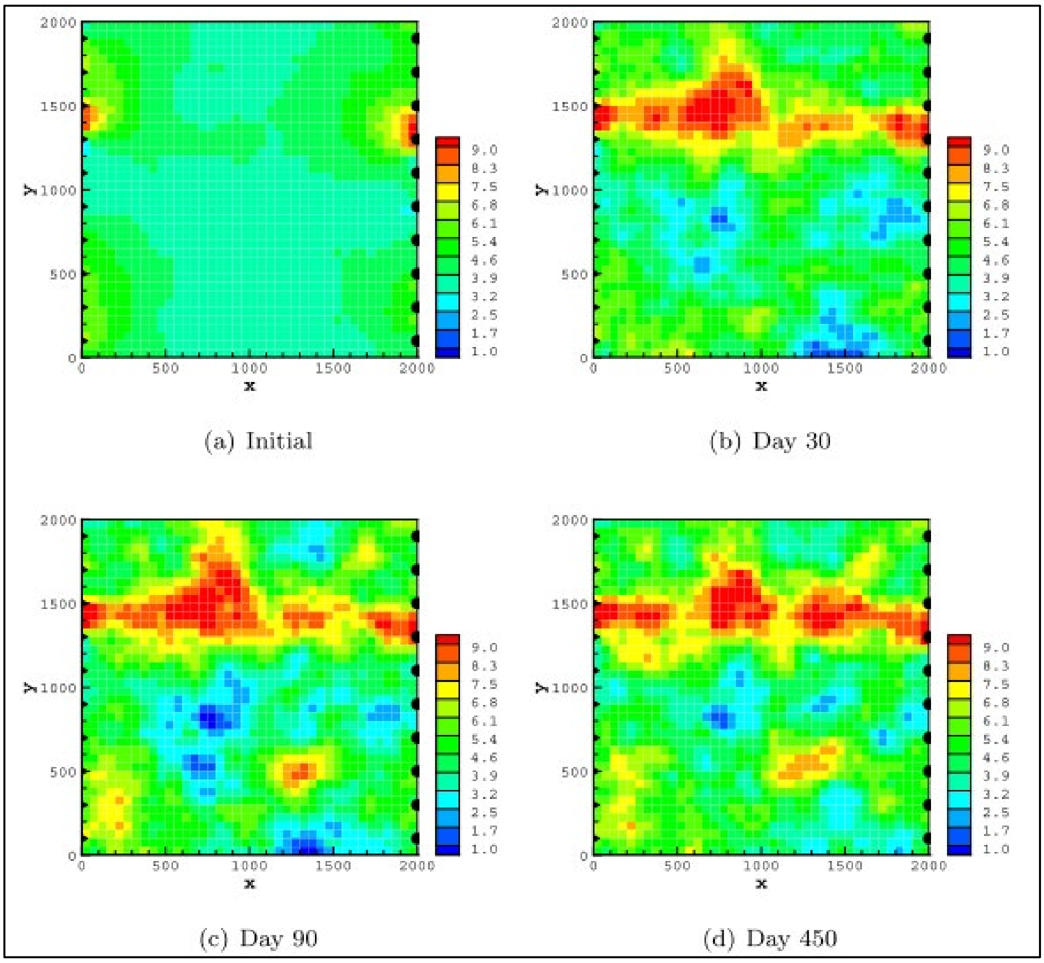

Figure 2. Mean of the initial $\ln k$ ensemble and mean of $\ln k$ ensemble updated at three different data times (Source: [12])

In our work we discuss results of implementation of the regularized Levenberg-Marquardt algorithm derived from minimum average cost (RLM-MAC [13]).

In study [13], the iterative Ensemble Smoother was applied to condition permeability field to well test data. 1D and 2D synthetic reservoir models were used to investigate the method performance with respect to measurement error and localization which we consider important from practical point of view.

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At first, authors analyzed the influence of measurement error. Despite of high accuracy of the modern pressure gauges, the pressure data are often quite noisy. In practice, various filtering, denoising and smoothing techniques are employed in order to clarify the reservoir response and reduce data uncertainty. They evaluated several cases with different variance of measurement error. The comparison revealed that the pressure data noise has strong impact on the parameter estimation and the method convergence. In many cases, the noise caused the ensemble drifting away from the true solution.

Another important practical aspect is localization of model updates. During well test, pressure transients reflect pressure propagation away from the well. The propagation dynamic is governed by the formation properties within the disturbed reservoir domain. Therefore, the pressure measurements at a given time may be used for updating formation properties in the model only within the disturbed domain around the well. This would lead to the conclusion that a localization technique may be employed to relate model updates to relevant observations representing response from different reservoir areas. A time/distance dependent localization technique was tested to address this problem. The testing results showed that the proposed localization technique allowed for better estimation of permeability distribution (in terms of discrepancy with the true case) (Figures 3-4). Results tell about potentially good implementation of this approach in CLRM.

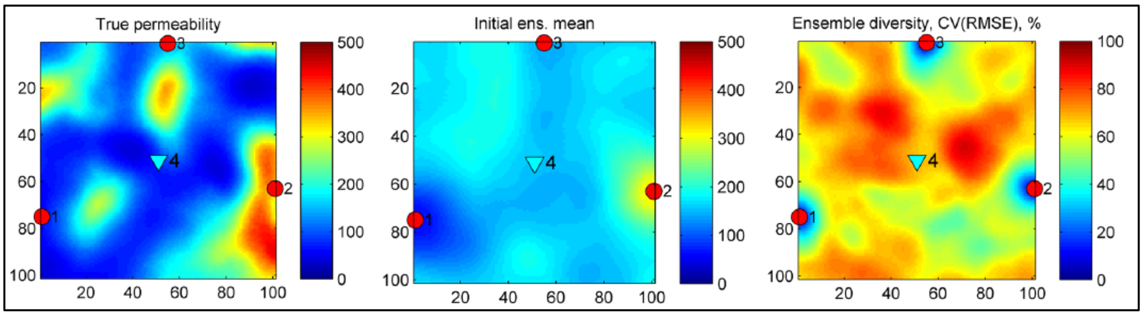

Figure 3. Initial ensemble (from left to right): a) true permeability distribution; b) ensemble mean; c) ensemble diversity (Source: [13])

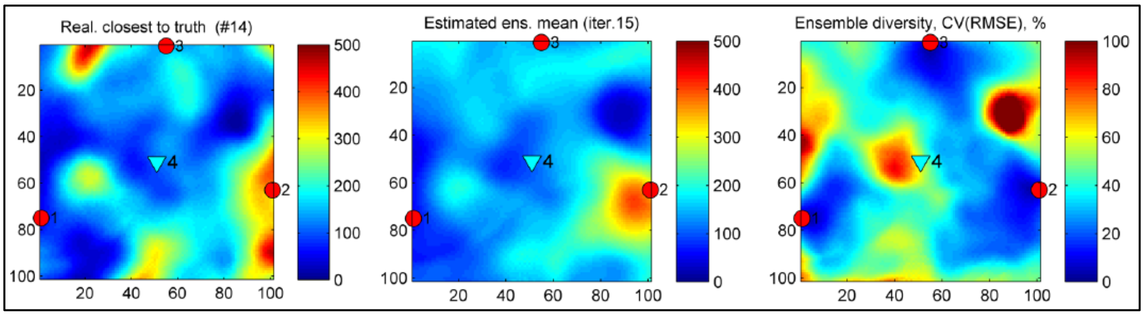

Figure 4. Conditioning with temporary localization (from left to right): a) realization closest to the true case; b) ensemble mean; c) ensemble diversity. (Source: [13])

3.3. Particle Filters

In the problem with nonlinear system, another method – particle filters offers the solution [14] for assimilate data. The main idea of this method is to approximate the prior and posterior probabilities using mixture of delta functions. The posterior is approximated by:

$$p(\theta \mid y) \approx \sum_{i=1}^{n} w_i \delta(\theta - \theta_i^a), \qquad (11)$$

where θ_i^a are the particles at the update step that are needed to represent the whole state space, w_i are the corresponding weights, and n is the particle size. The particle filter method consists of the following steps:

Prediction step: The particles θ_i^a are evolved forward in time using the dynamical model to obtain the forecast estimates θ at the next time step. The corresponding weights w_i remain the same.

Filtering step: The particles remain the same. The weights are updated when receiving a new observation using Bayes rule.

Re-sampling step: In practice, the particle filter may have problems related to the weights known as weight collapse [14], especially for high-dimensional problems. You may have seen results of implementation of particle filtering in work [15] (Fig. 5-6).

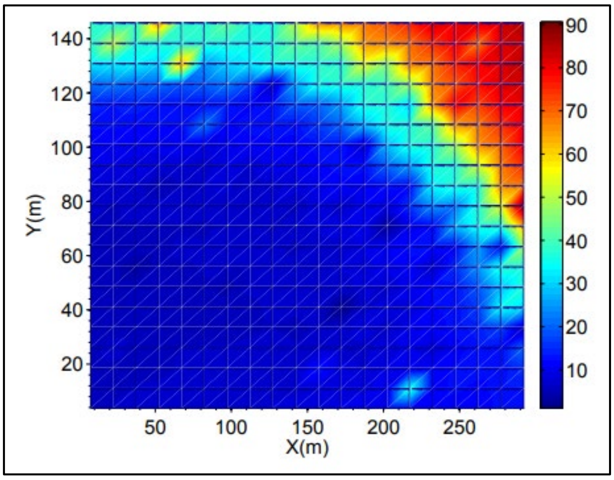

Figure 5. An initial ensemble of the absolute permeability field (Source: [15])

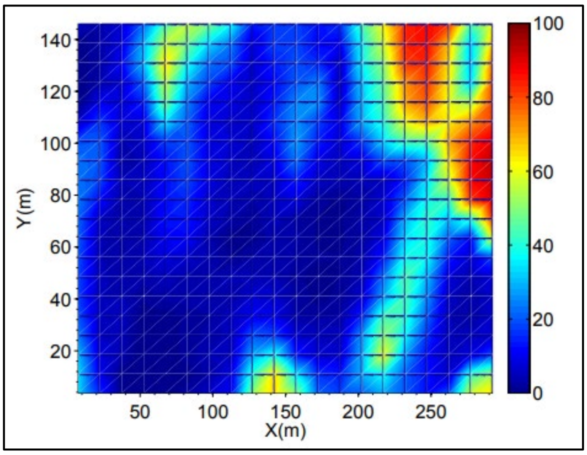

Figure 6. Estimates of absolute permeability fields at final time step using PF (Source: [15])

As can be seen, the permeability estimate is quite good, but it is necessary to conduct more numerical experiments to analyze the effectiveness of particle filters, but however this approach is applicable for CLRM.

4. Conclusions

Different methods, algorithms and approaches can be applied to assimilate different types of data (production data, well test data, seismic data).

- The most studied approach – Ensemble Kalman Filtering (EnKF) has very good results in data assimilation, but there is no sufficient research for evaluation of different schemes of EnKF such as: stochastic EnKF, singular evolutive interpolated KF, etc.

- Regarding the ensemble smoothing method the following should be noted: more research needed for evaluating the spatial/ temporal localization of the gain matrix for preventing ensemble collapse and retained ensemble diversity; studies about temporal localization based on the maximal extent of the disturbed domain over the entire ensemble; update of the localization matrix after each iteration.
- Particle filters contain the promise of fully nonlinear data assimilation. Method have been applied in numerous science areas, including geoscience, however, application of PF to high-dimensional geoscience systems has been limited due to its efficiency in high-dimensional systems in standard settings. However, huge progress has been made, and this limitation is disappearing fast due to recent developments in proposal densities, the use of ideas from (optimal) transportation, the use of localization and intelligent adaptive resampling strategies. However, more studies with implementation of PF to CLRM are required in the future.

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