Ensemble Information Filter for Seismic-Horizon History Matching: Plausible, Spatially Coherent Updates without Tuning

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Objective

Test the **Ensemble Information Filter** – EnIF,

with a **Smoother** implementation

in performing **Assisted History Matching** – AHM

of **Oil and Gas Reservoir flow models**

including **2D surfaces** as uncertain parameters.

Lunde, B. Å. S., An Ensemble Information Filter: Retrieving Markov-information from the SPDE discretisation, https://arxiv.org/abs/2501.09016

Internal

EnIF approach

Two ways to represent the parameter update…

Ensemble Smoother ⟷ **Ensemble information filter (smoother)**

$$K^f = C^f_{xy}\left(C^f_{yy} + C_\varepsilon\right)^{-1}$$

↓

$$\boldsymbol{x}^a_i = \boldsymbol{x}^f_i + \boldsymbol{K}^f\left(\boldsymbol{d}_i - \boldsymbol{\mathcal{H}}\left(\boldsymbol{x}^f_i\right)\right)$$

Definitions (for completeness)

$$y_i = \mathcal{H}\left(x^f_i\right) \approx Hx^f_i + e^f_{h,i}$$

$$K^f = C^f_{xd}\left(C^f_{dd} + C_\varepsilon\right)^{-1} \approx C^f_{xx}H^T\left(HC^f_{xx}H^T + C_\varepsilon\right)^{-1}$$

$$C^{-1}_{xx} = \Lambda_{xx}$$

$$C^{-1}_{\varepsilon} = \Lambda_{\varepsilon}$$

Perturbed observations: $d_i \sim N(d, C_\varepsilon)$

All variables are assumed to be standardized

Convert parameters to information form: $\eta^f_i = \Lambda^f_{xx}x^f_i$

↓

Update the precision matrix: $\Lambda^a_{xx} = \Lambda^f_{xx} + H^T\Lambda_\varepsilon H$

↓

Update the parameters in information form: $\eta^a_i = \eta^f_i + H^T\Lambda_\varepsilon d_i$

↓

Return parameters to original form: $\boldsymbol{x}^a_i = \left(\boldsymbol{\Lambda}^a_{xx}\right)^{-1}\boldsymbol{\eta}^a_i$

Where Localization Comes From in EnIF

Localization via sparsity

Sparsity in $\boldsymbol{H}$

$$\mathcal{H}(x_i^f) \approx H x_i^f + e_{h,i}^f$$

Linear regression with LASSO-like regularization:

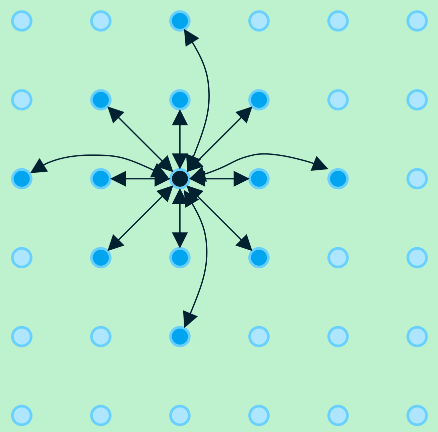
- promotes sparsity via ℓ_1-penalization
- automatic feature selection and reduced overfitting
- computationally demanding in high dimensions

In practice:

Fewer parameter-data links
↓
Updates focus on the most relevant interactions

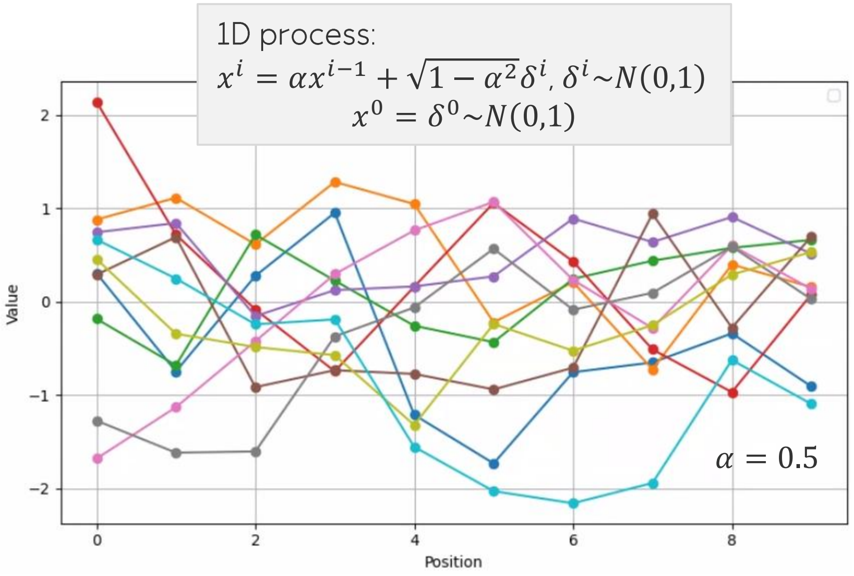
Sparsity in $\boldsymbol{\Lambda_{xx}^f}$

- Graph defines sparsity of the prior precision matrix
- Relevant for spatially distributed parameters
- Conditional dependence is restricted to neighbours up to the chosen order
- Order 2 example:

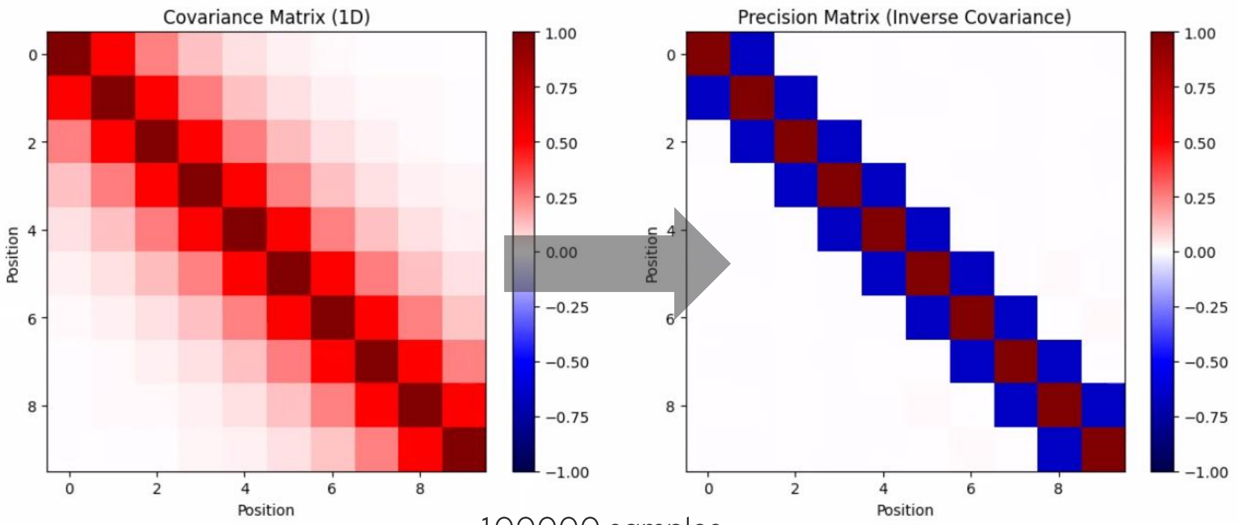


$\longleftrightarrow$ Edge ⇄ nonzero entry in the precision matrix

Precision matrix structure – a quick 1D example

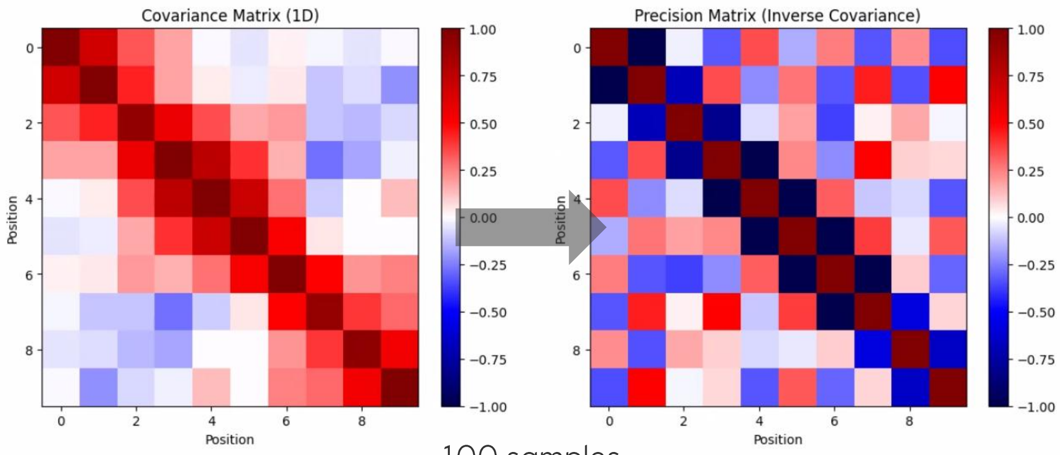


"Infinite" ensemble estimate



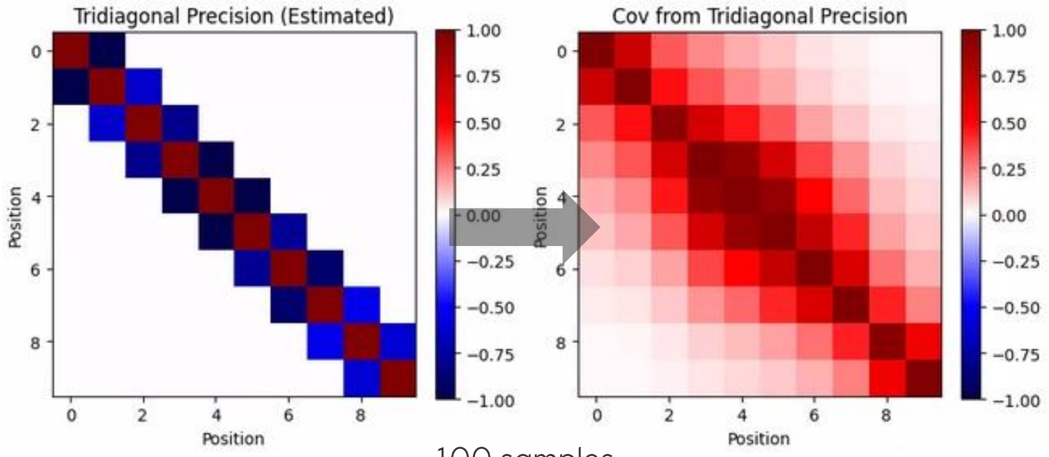
100000 samples

Finite ensemble estimate of the covariance (no structure was imposed)



100 samples

Finite ensemble estimate of the precision (tridiagonal structure was imposed)



100 samples

Methods Evaluated

1. Distloc
2. Adaptive
3. EnIF

Ensemble Smoother

$$x_i^a = x_i^f + \left\{\rho \circ \left[C_{xd}^f\left(C_{dd}^f + C_D\right)^{-1}\right]\right\}\left[d_i - \mathcal{H}\left(x_i^f\right)\right]$$

ρ: localization (elementwise tapering of the gain)

1 Distance-based

$$\rho_{j,k} = f(r_{j,k})$$
$$r_{j,k} = \|x_j - d_k\|$$

- $r_{j,k}$: Euclidean distance between a parameter j and a data k.
- The centre of the well is taken as the origin of the data.
- Gaspari-Cohn function to compute tapering.
- No tapering of scalar parameter links

2 Correlation-based

$$\rho_{j,k} = \begin{cases} 0, if \ |\mathrm{Corr}(x_j, d_k)| < c \\ 1, if \ |\mathrm{Corr}(x_j, d_k)| \geq c \end{cases}$$

- Hard-threshold localization based on sample correlations
- $c = \frac{3}{\sqrt{N_e}}$
- N_e is the ensemble size

3 Ensemble Information Filter

$$\Lambda_{xx}^a = \Lambda_{xx}^f + H^T \Lambda_\varepsilon H$$
$$\eta_i^a = \eta_i^f + H^T \Lambda_\varepsilon d_i$$
$$x_i^a = (\Lambda_{xx}^a)^{-1} \eta_i^a$$

Λ_{xx}^f estimate of the parameter precision matrix from the prior ensemble

- Estimated using a predefined graph structure
- Assumes a Markov structure with order 2 neighbourhood

H: estimate of the linearized observation operator (via regression)

- Boosting-based monotone LASSO with information-theoretic early stopping

Software tools used in this study

FMU
Fast Model Update

RMS
aspentech

Modelling:
- Structural
- Facies
- Property
- Well

Visualization

Reservoir flow simulation

OPM
OPEN POROUS MEDIA

ert

Analysis – parameter update
Workflow management

graphite-maps

EnIF algorithms

XTGeo Manipulation of (oil industry) subsurface reservoir modelling

pyscal Generating and formatting relative permeability and SCAL data

Open source

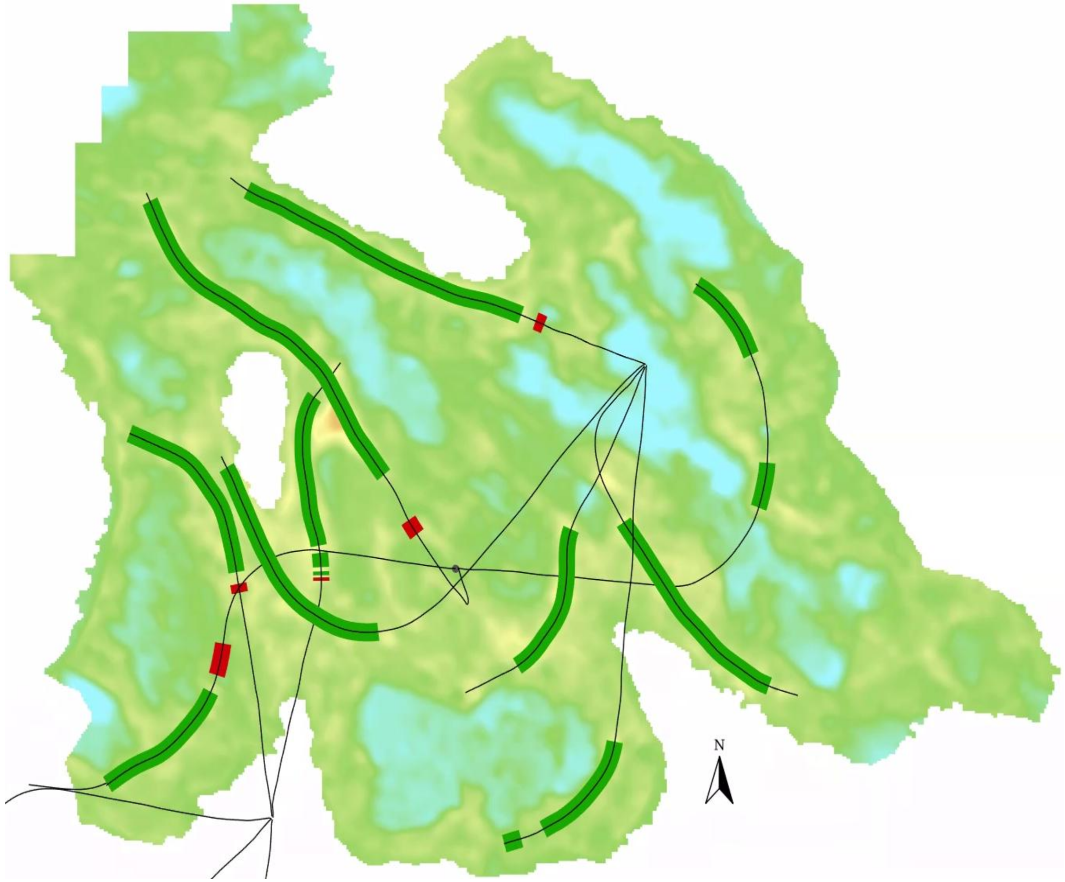
Visualization tools

Webviz

ResInsight

Study case 1

- Offshore Oil field
- Average depth of the reservoir top: 1750 m
- Excellent permeability and porosity
- 17 wells
    - Controlled in history by oil production (lower uncertainties)
- Typical oil column: 10-30 m
- Main reservoir modelling challenges:
    - Represent water production (coning)
    - Represent pressure depletion and aquifer support



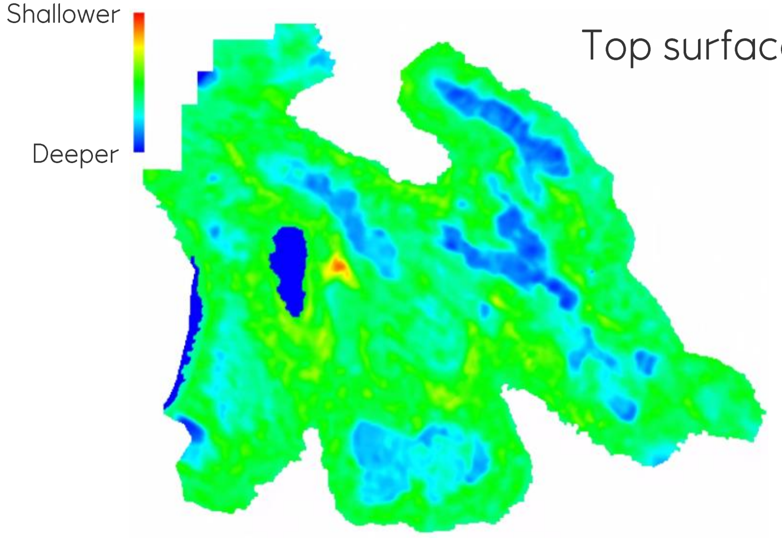
Study case 1

AHM setup – parameters

Top surface mean and standard deviation

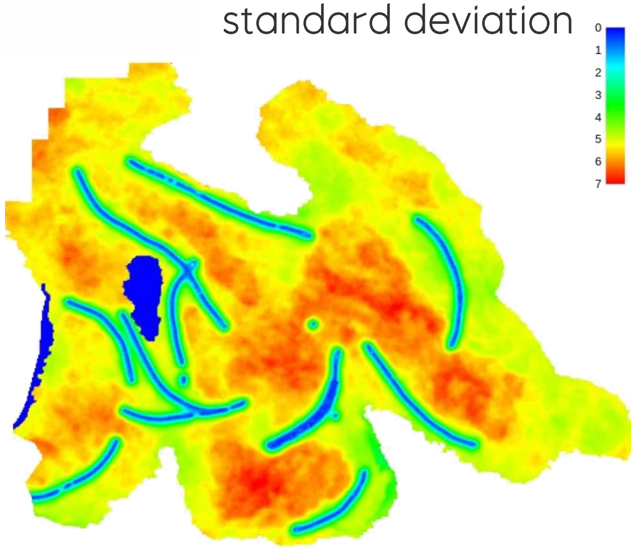
Scalar: 60

- Static parameter multipliers (e.g. permeability and porosity)
- Relative permeability parameters
- Oil viscosity per PVT region
- FWL per equilibrium region
- Aquifer communications
- Facies model parameters
- J-function parameters
- Others



Top surface mean

Top surface standard deviation



Uncertainty along the wells is negligible due to ultra-deep resistivity data

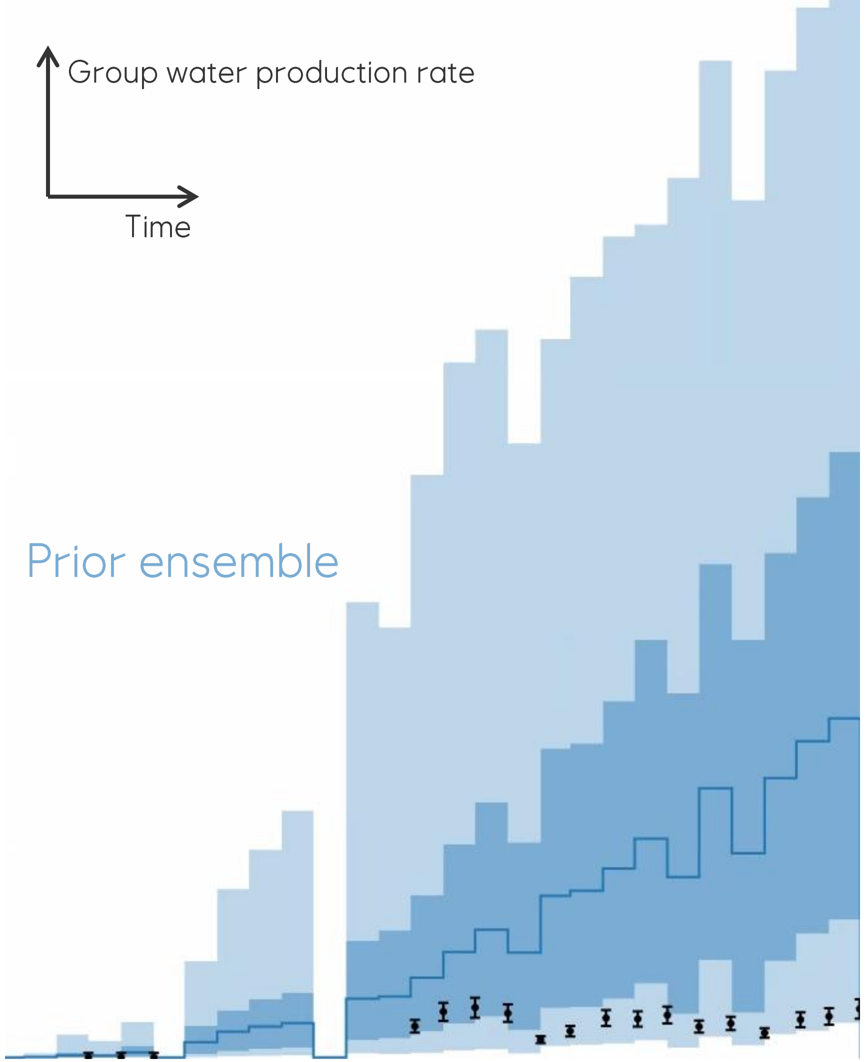
Surface: 503272

- Seismic horizon defining the top of the reservoir
- Input for the structural modelling workflow

Study case 1

AHM setup – 242 observations

Well shut-in pressures	Well water-cut
Group water production rate	Aquifer pressure

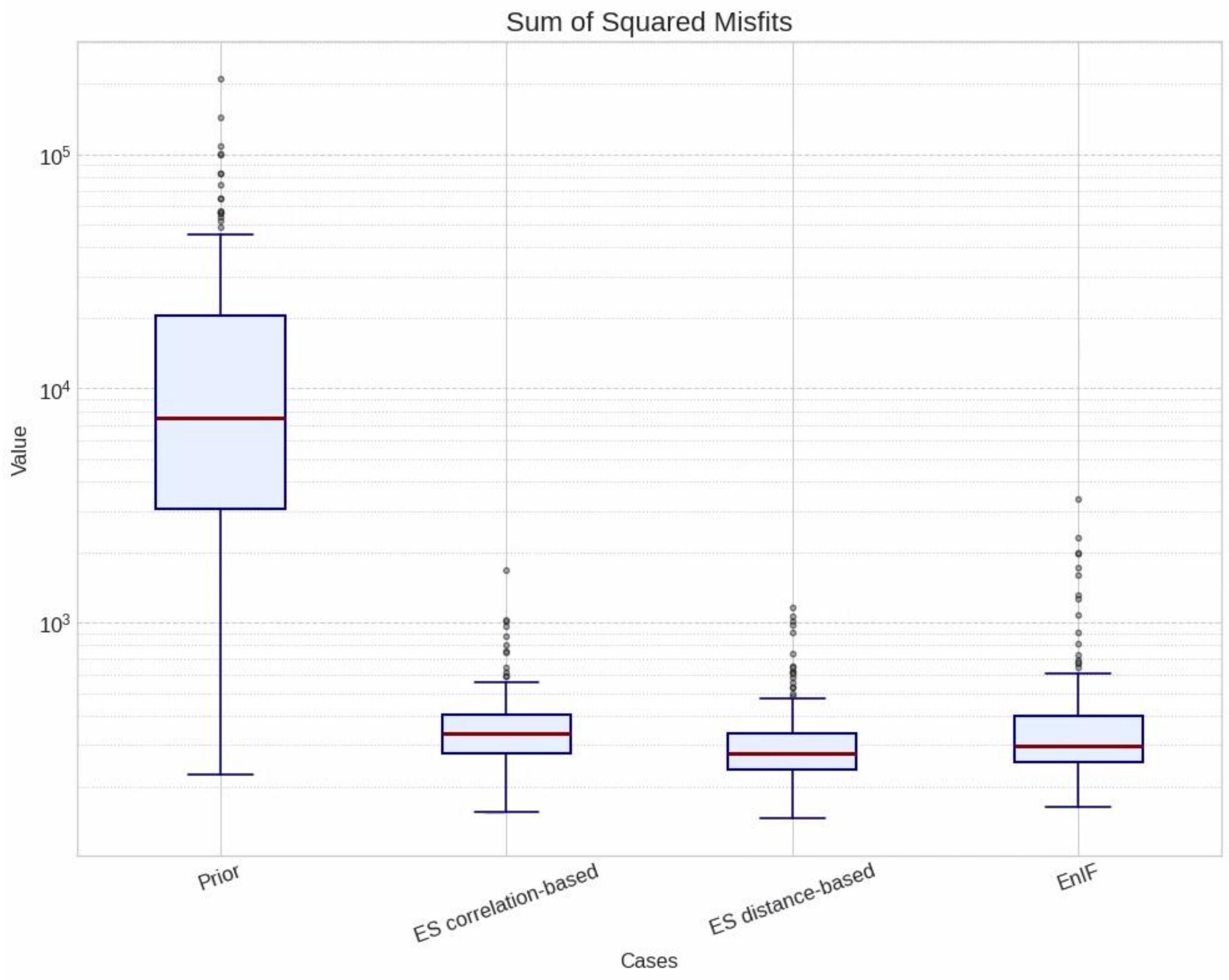


Study case 1 – results

Misfit of observation k in realization i:

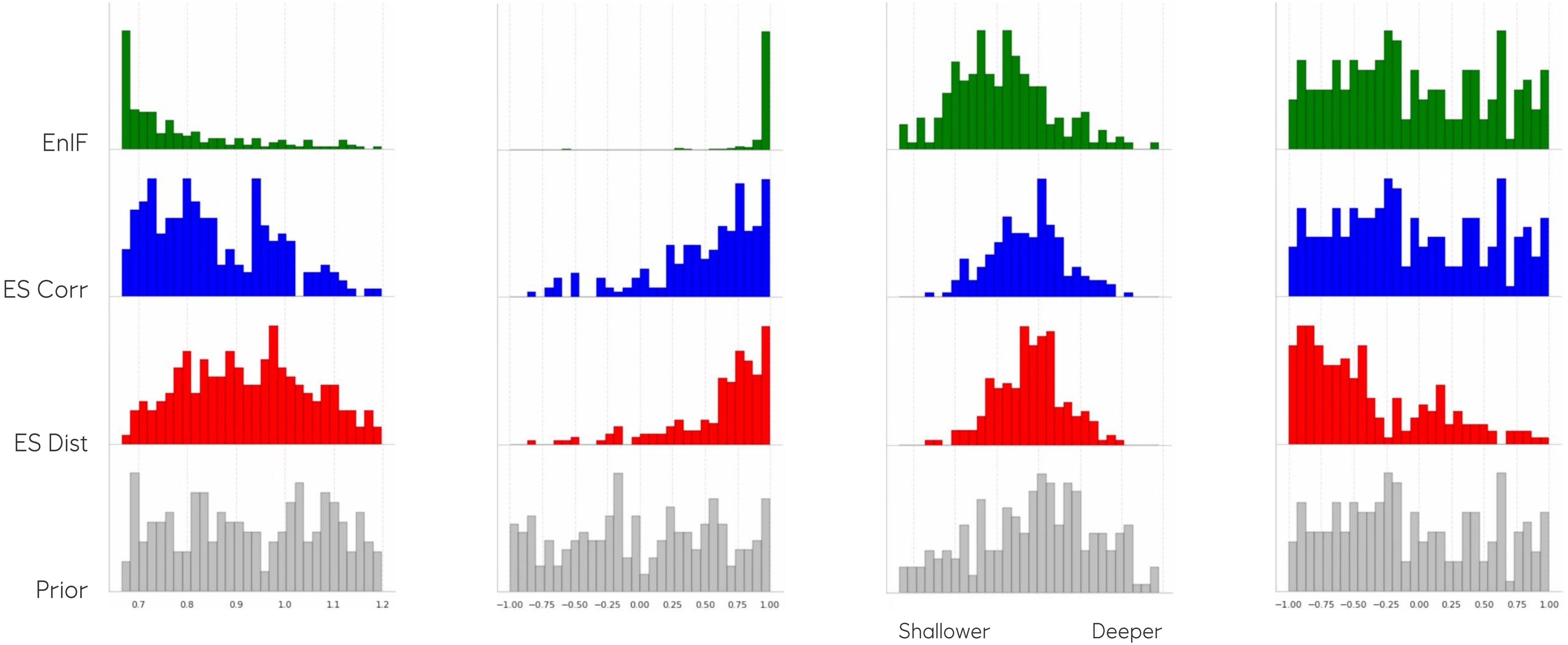
$$\delta_{i,k} = \frac{\left(d_k - \mathcal{H}(x_i)\right)^2}{\sigma_k^2}$$

Misfit reduction with a 1-step update



Study case 1 – results – scalar parameter updates

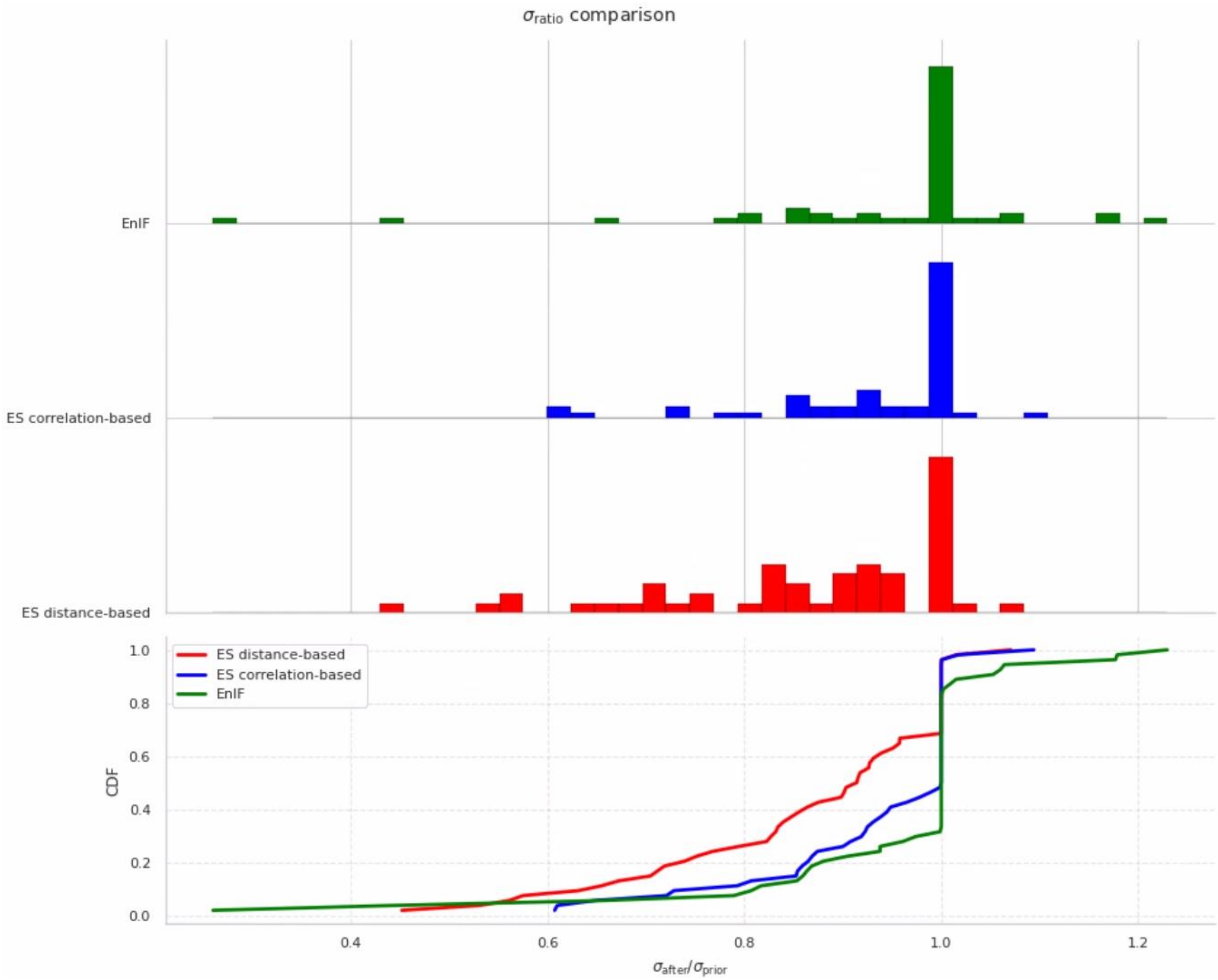
Oil viscosity multiplier example | Water-oil relative permeability interpolation parameter | FWL example | Gas-oil relative permeability interpolation parameter



Study case 1 – results – scalar parameter updates

The distance-base case updates scalar parameters without localization.

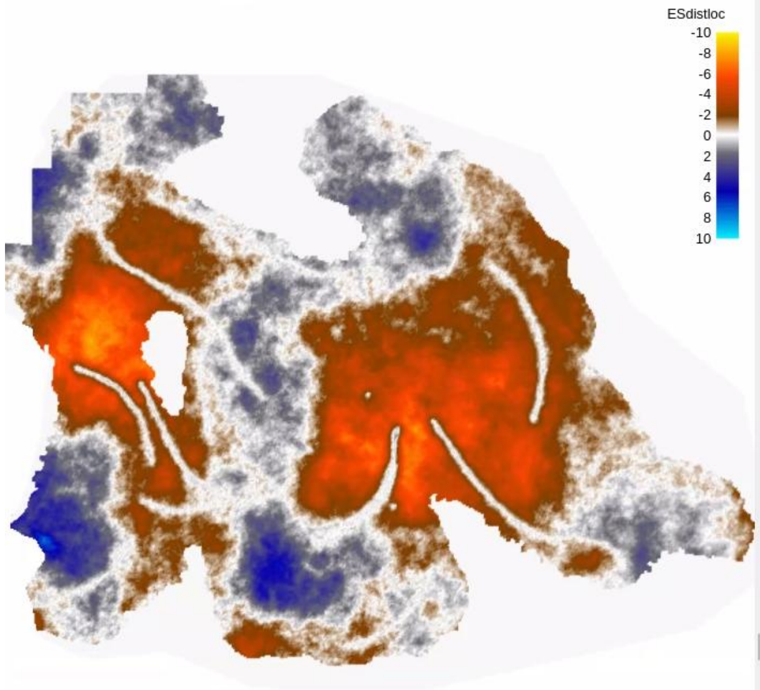
EnIF is selective on which parameters to update, but it updates strongly the selected ones.



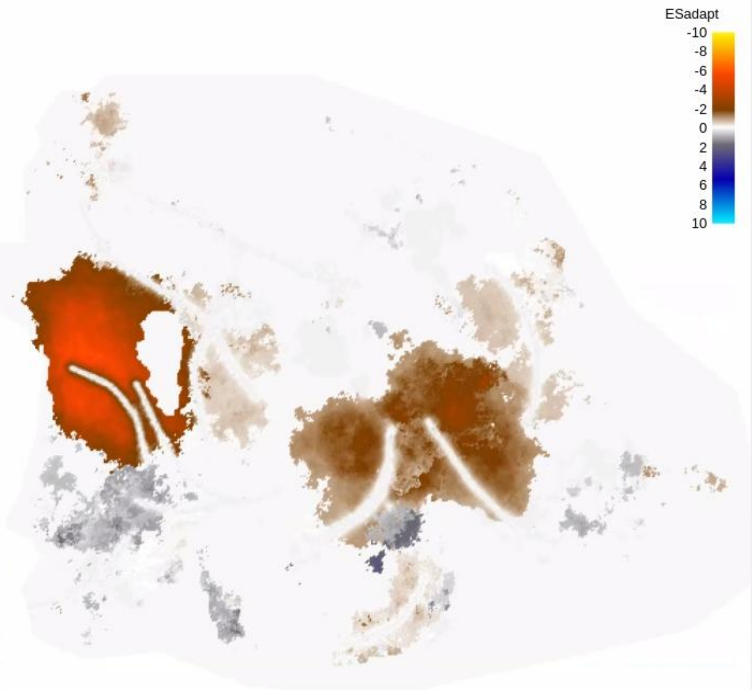
Study case 1 – results – surface updates

Ensemble average update

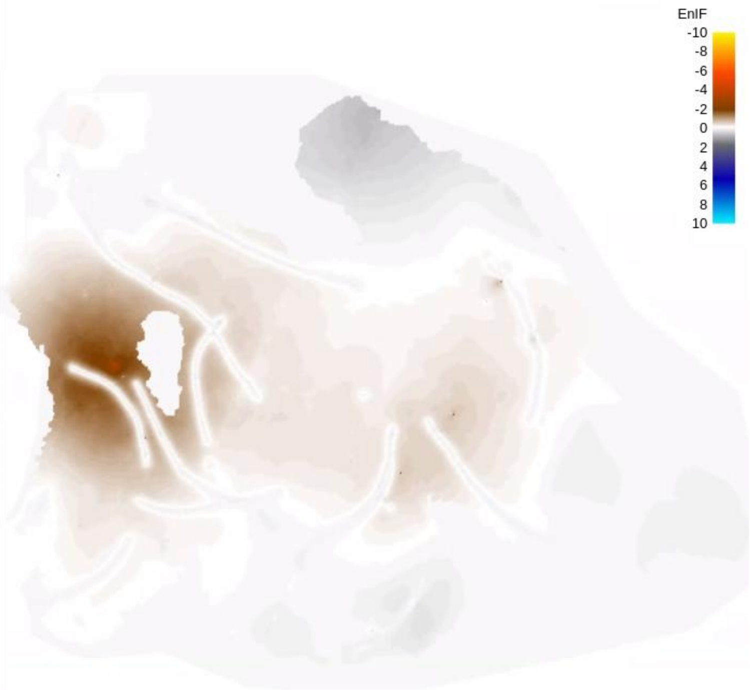
ES distance-based localization



ES correlation-based localization



EnIF



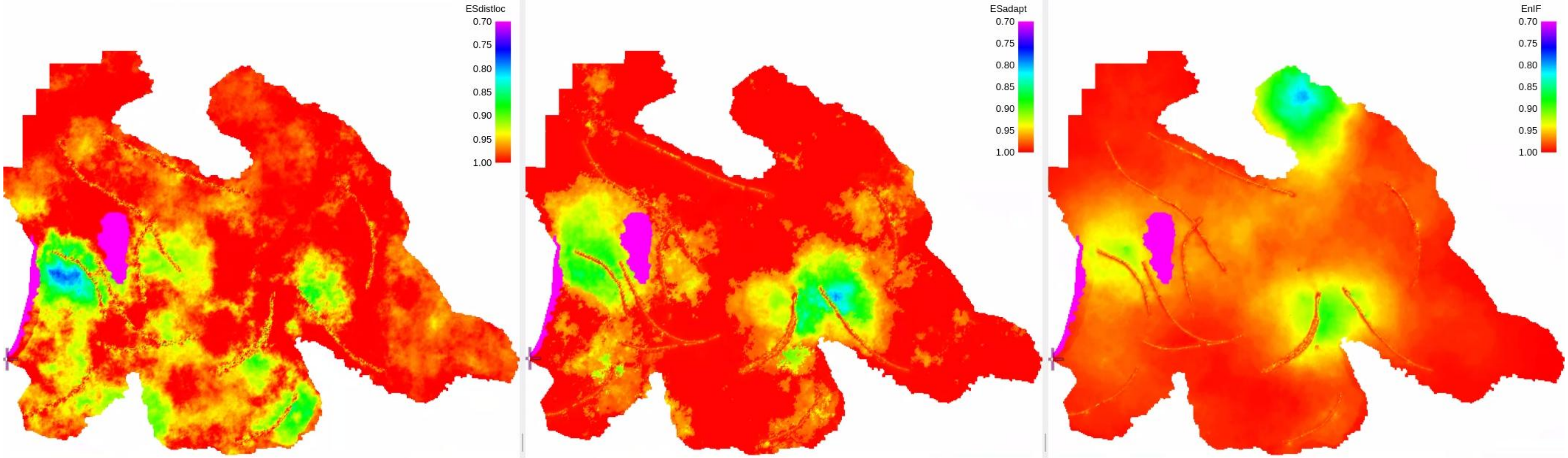
Study case 1 – results – surface updates

Standard deviation ratio: $\sigma_{updated}/\sigma_{prior}$

ES distance-based localization

ES correlation-based localization

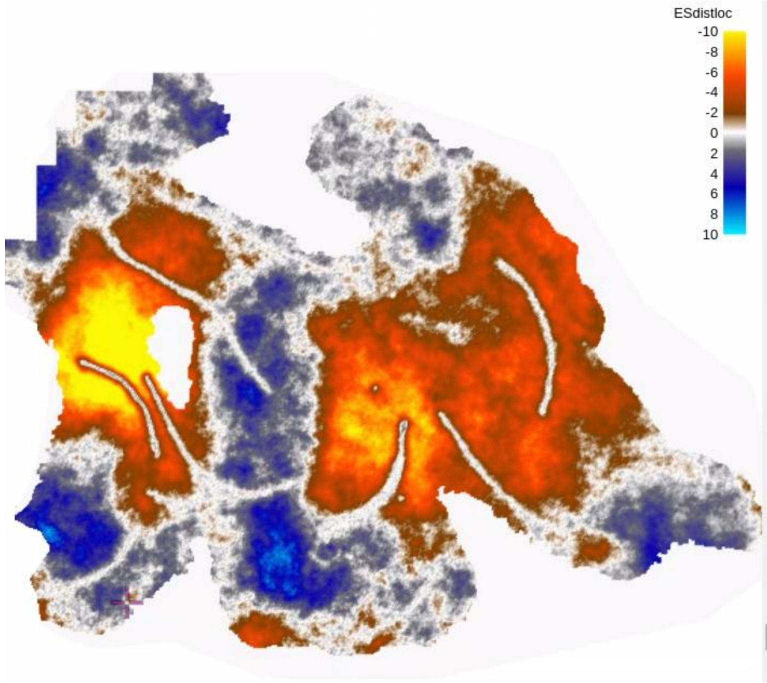
EnIF



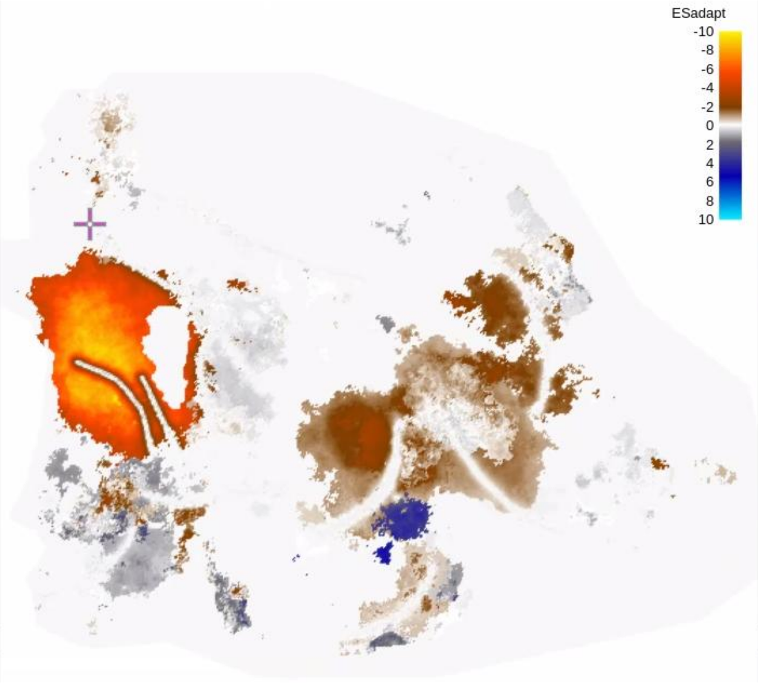
Study case 1 – results – surface updates

Realization 199 update

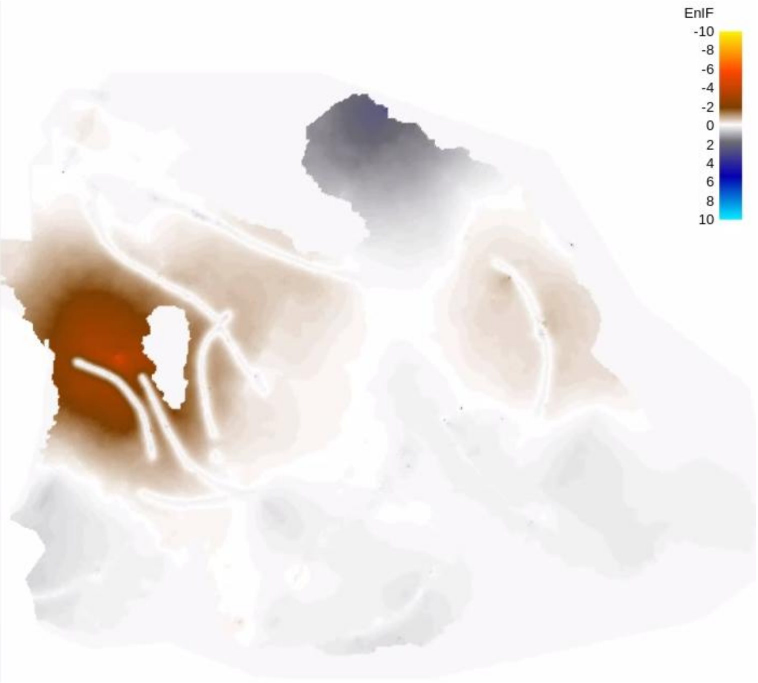
ES distance-based localization



ES correlation-based localization



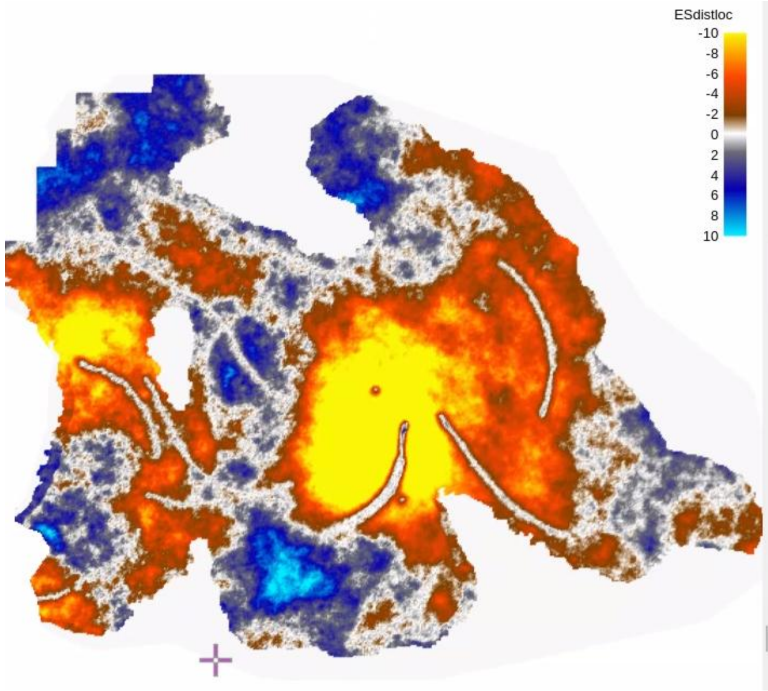
EnIF



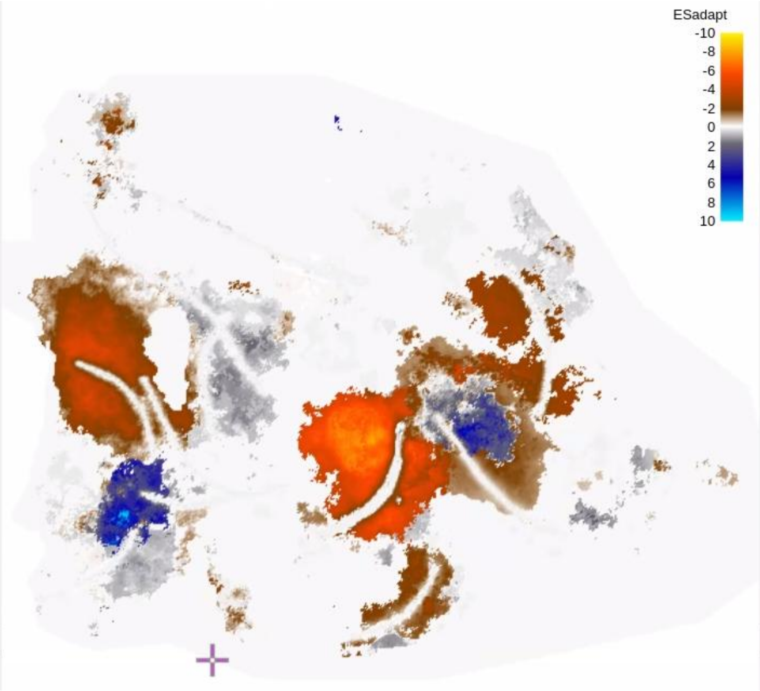
Study case 1 – results – surface updates

Realization 7 update

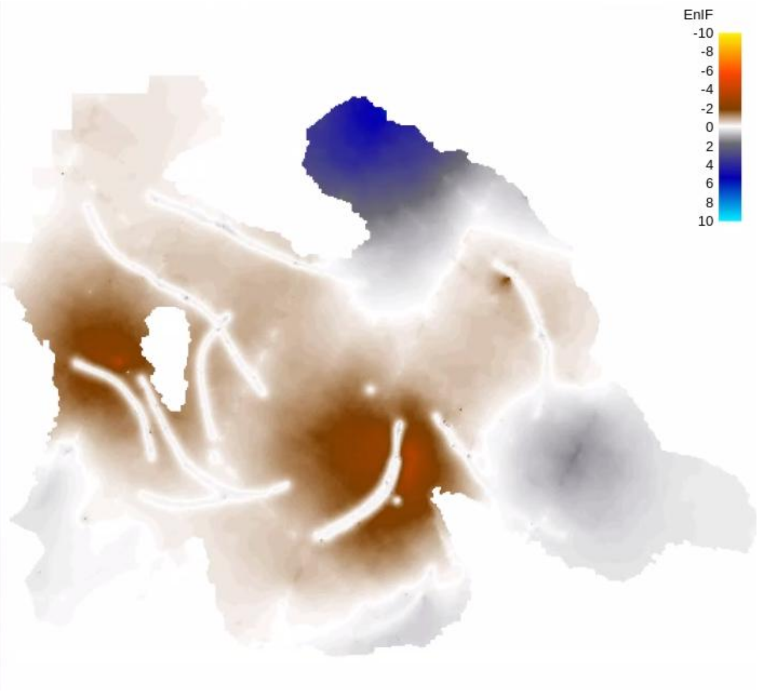
ES distance-based localization



ES correlation-based localization

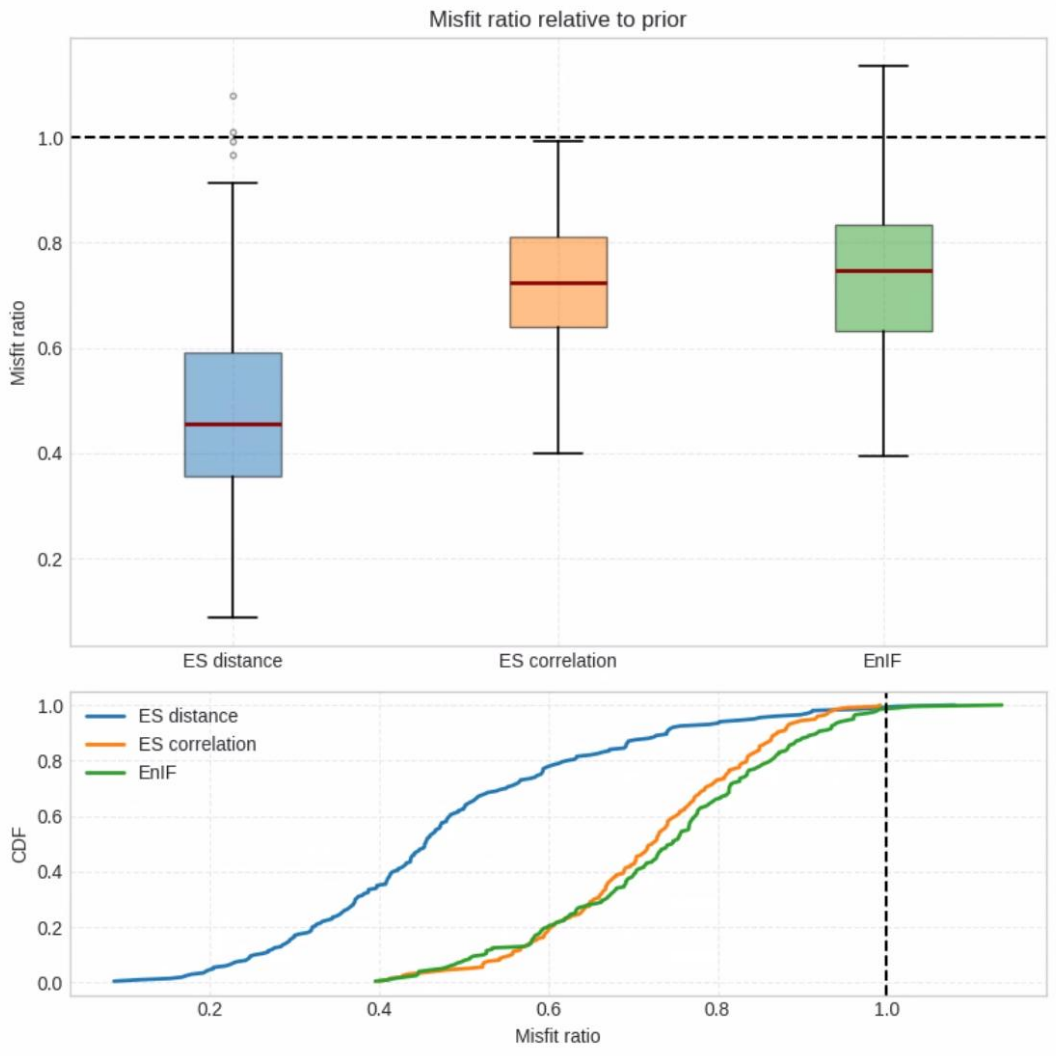


EnIF



Study case 1 – results – surface updates

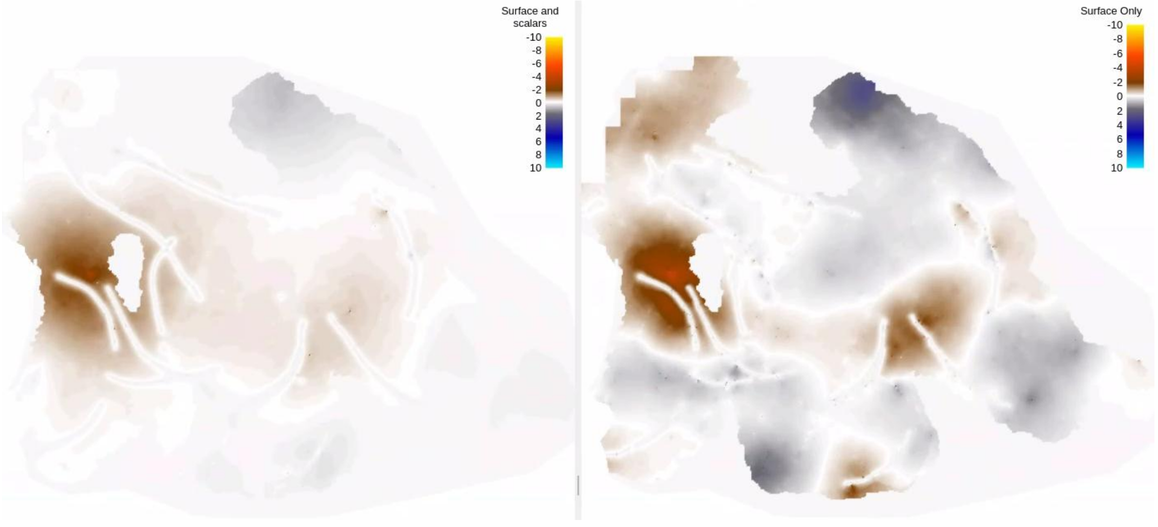
Updating only the surface



EnIF

Scalars and surface

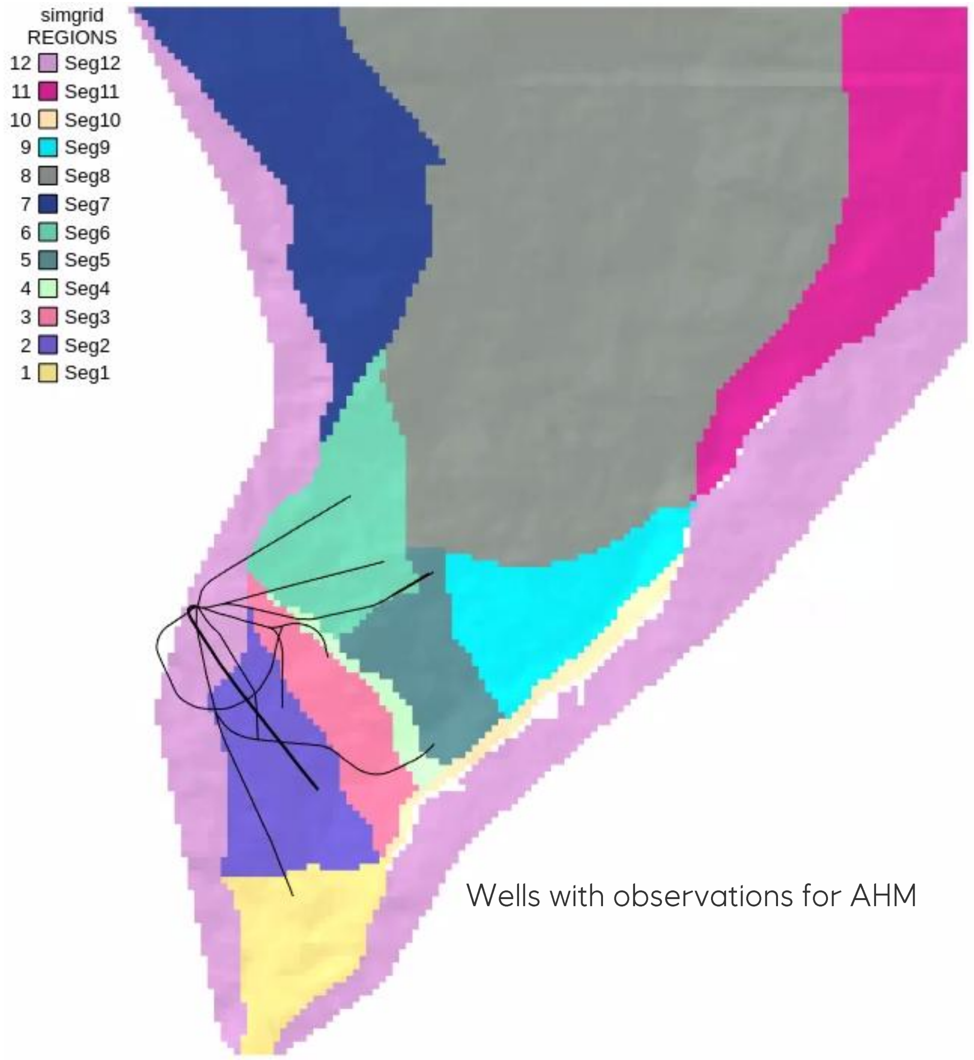
Surface only



Even if the responses are the same, changing the available parameters changes EnIF updates of the remaining.

Study case 2

- Reservoir and the model
  - Oil reservoir
  - 1.1 million cells
  - Wells: 2 injectors, 6 producers
  - Dummy wells to mimic open boundary in the north and south of the grid
  - Channels play a key role
  - Many faults and connectivity uncertain across the fault blocks
  - **Very noisy case**
- Parameters
  - Scalars – 187
    - Fault transmissibility, inter-region/zone communication, relative permeability parameters, FWL, among others
  - Seismic horizons (5 surfaces) – 510120
- Observation data – 45
  - Shut-in pressure
  - Well water-cut
  - Oil and gas production volumes



Wells with observations for AHM

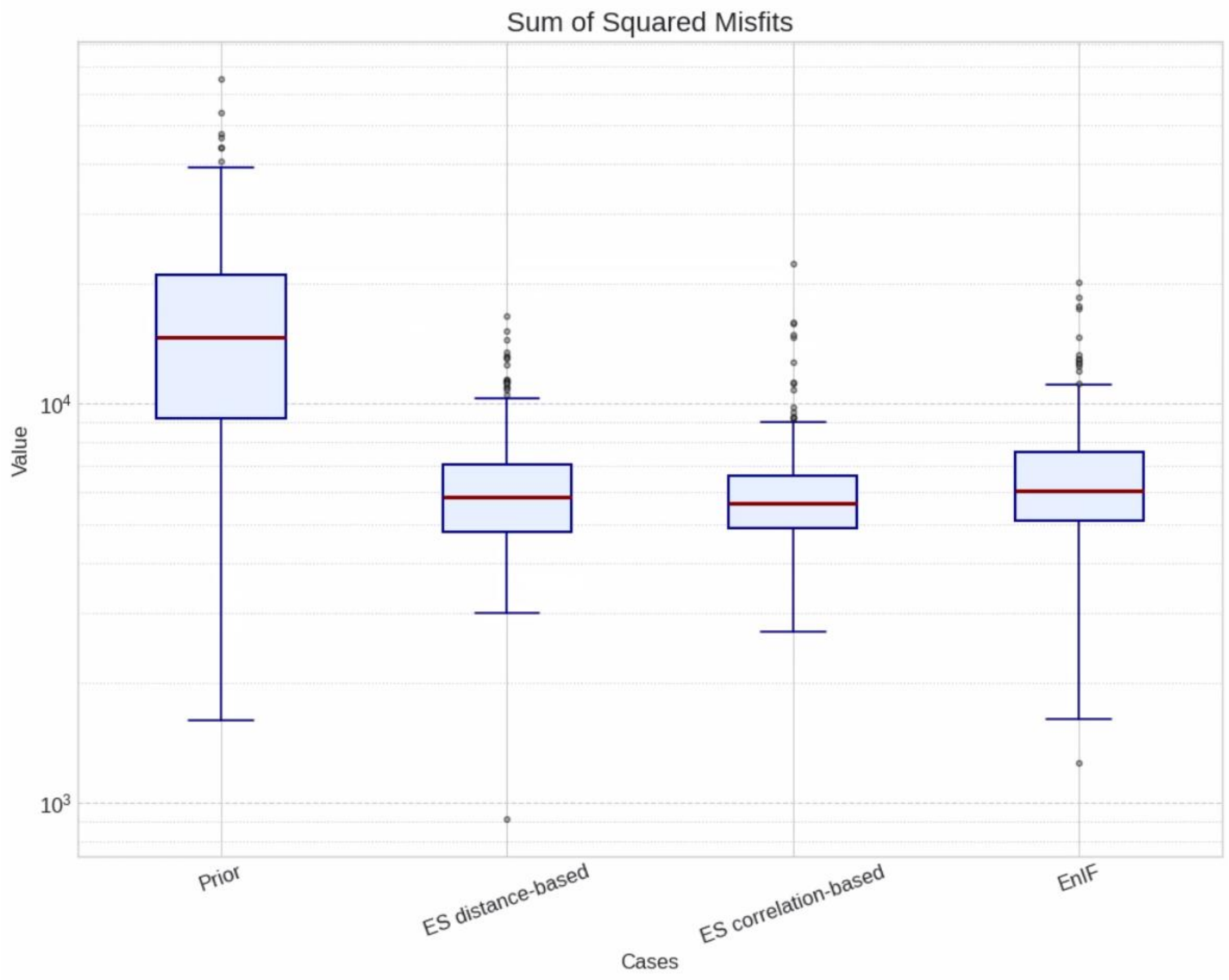
Internal
16 June 2026

Study case 2 – results

Misfit of observation k in realization i:

$$\delta_{i,k} = \frac{\left(d_k - \mathcal{H}(x_i)\right)^2}{\sigma_k^2}$$

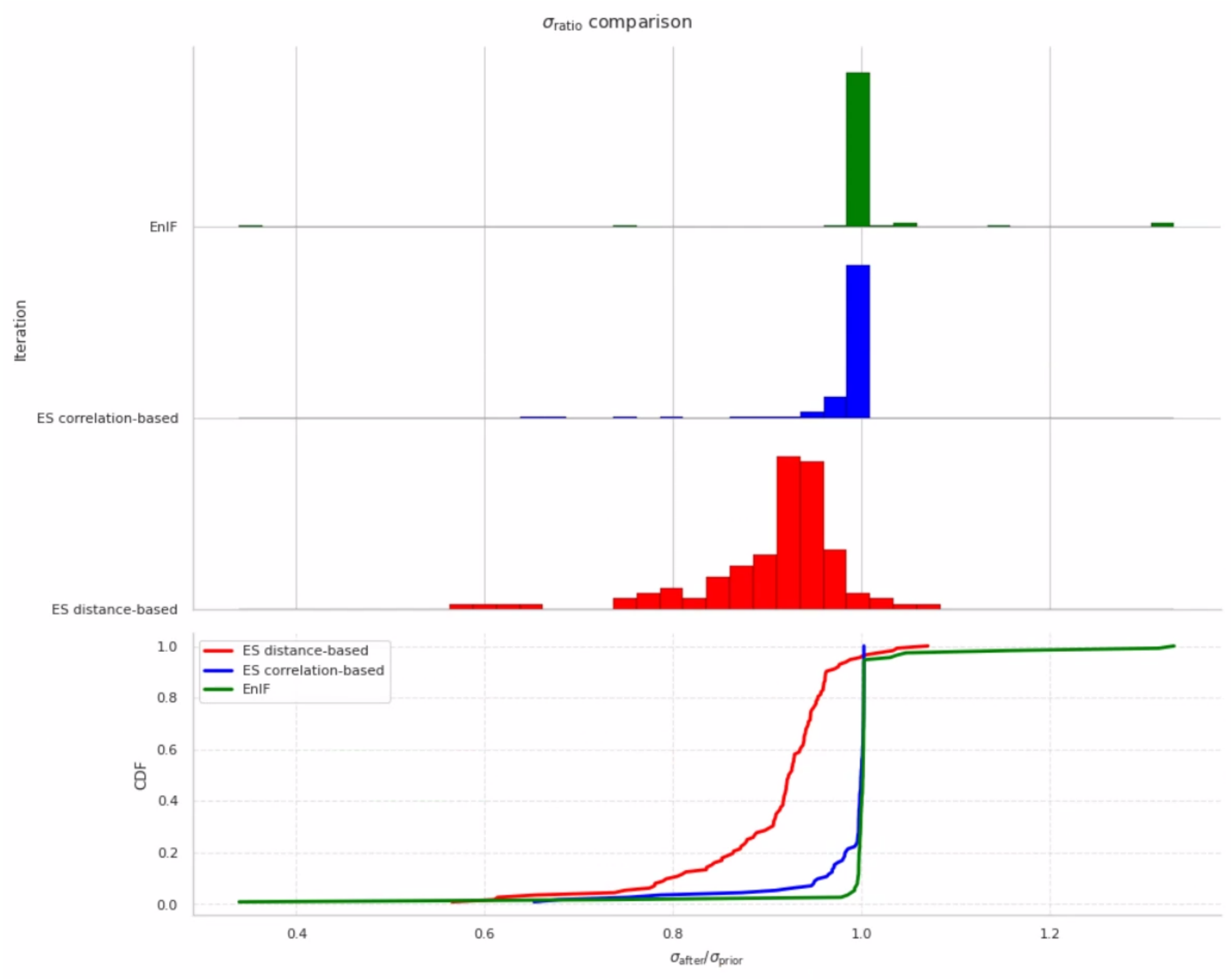
Misfit reduction with a 1-step update



Study case 1 – results – scalar parameter updates

Very few parameter updates in 1-step update.

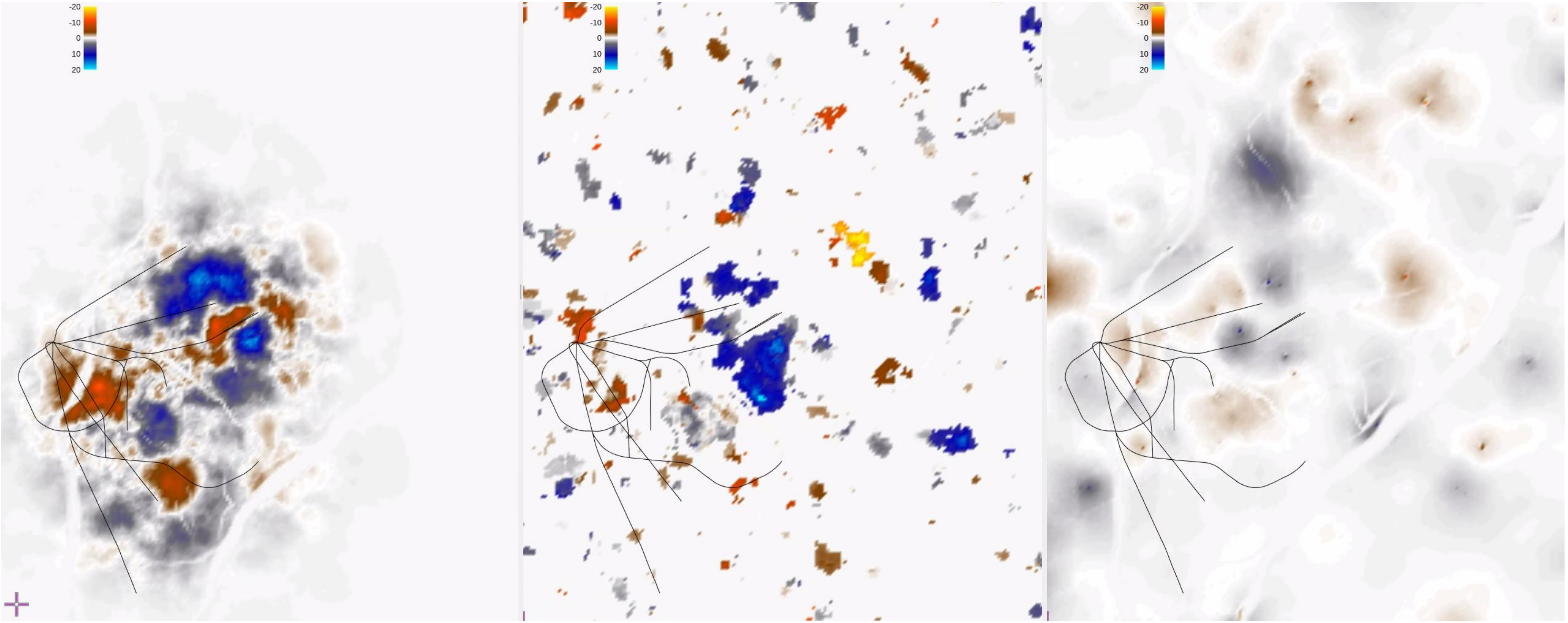
MDA could potentially improve this result.



Study case 2 – results – surface updates

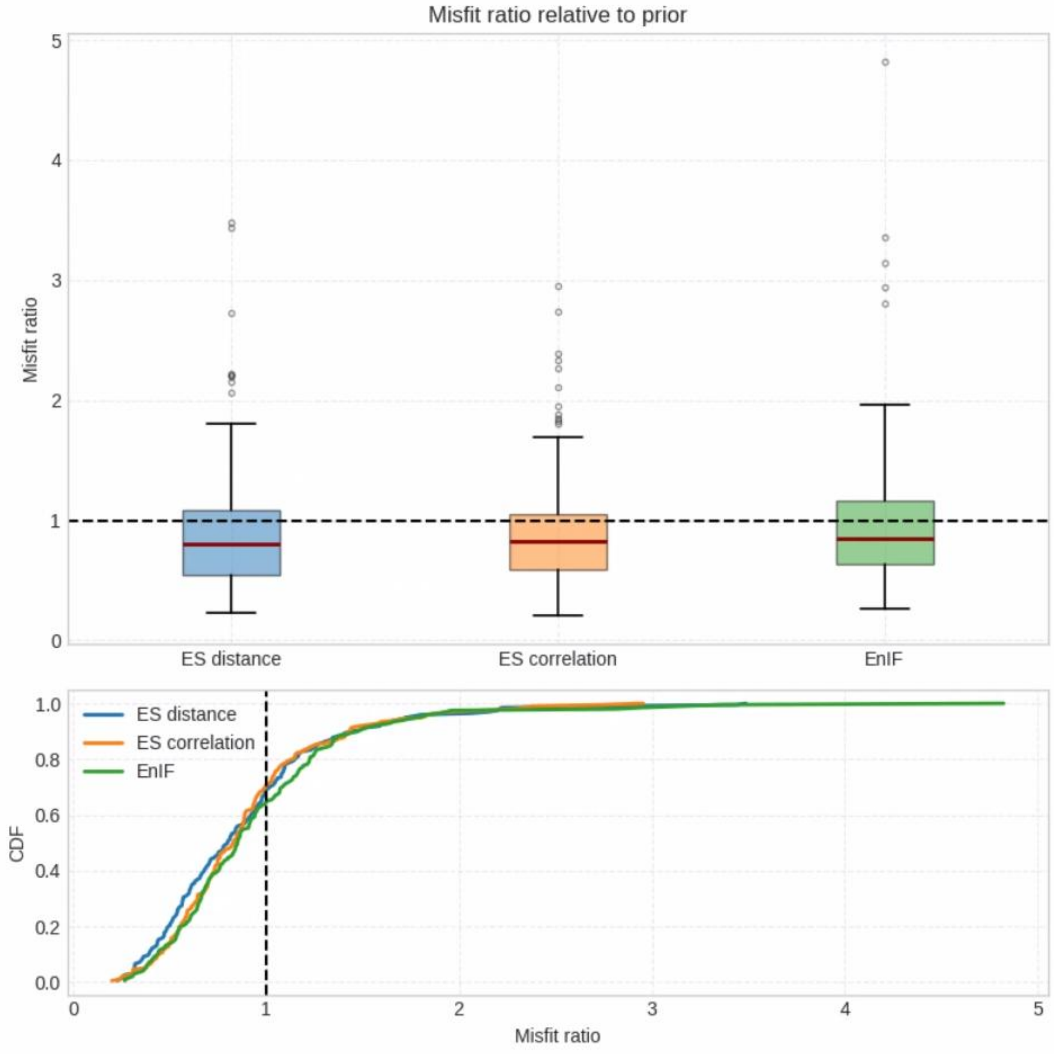
Ensemble average update

ES distance-based localization | ES correlation-based localization | EnIF



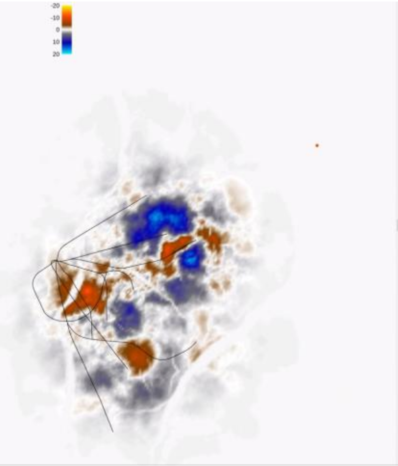
Study case 2 – results – surface updates

Updating only the surfaces

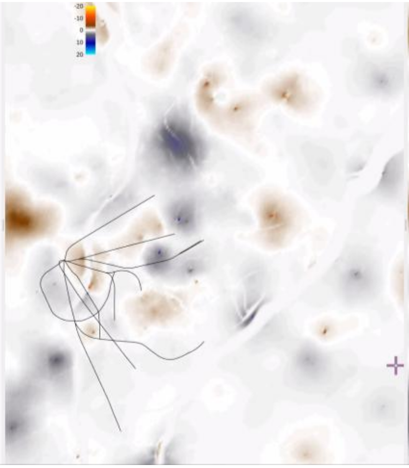


Ensemble average update

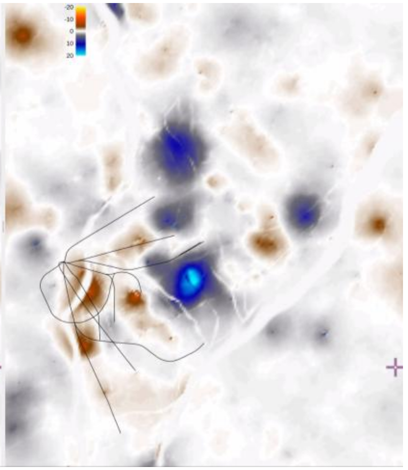
Distance-based



EnIF Scalar Surf



EnIF Surf only



Conclusions and future work

Our implementation of Ensemble Information Filter (EnIF) provided **misfit** reduction comparable to ES with distance or correlation-based localization.

When updating **scalar** parameters, EnIF was the most selective method. However, it results in strong updates of the selected parameters.

When updating **surface** parameters (2D), EnIF mostly provided local and smooth updates around the wells.

- The intensity of surface updates were more subtle than ES

Removing updatable parameters (keeping the prior responses) changes how EnIF will update the remaining parameters.

- The method finds more links in the H matrix and provides more updates

In the very **noisy** case, ES with adaptive localization provided noisy updates scattered all over the surface. In this case, EnIF also provided spurious updates, but attenuated and smoother when compared to the former.

In conclusion, ES-MDA with localization remains our recommended approach for history matching reservoir models; **HOWEVER**, EnIF shows strong potential and is well worth continued research and further testing.

Future work

Implement and test EnIF-MDA

Investigate more efficient algorithms to estimate the parameter precision matrix.

Continue investigating regression solutions that favours a sparse H but can select important links between parameters and responses.

When computationally feasible, investigate 3D parameter updates with EnIF.

Acknowledgements

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Questions?

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