Feature-oriented Joint Time-lapse Seismic and Electromagnetic History Matching Using Ensemble Methods

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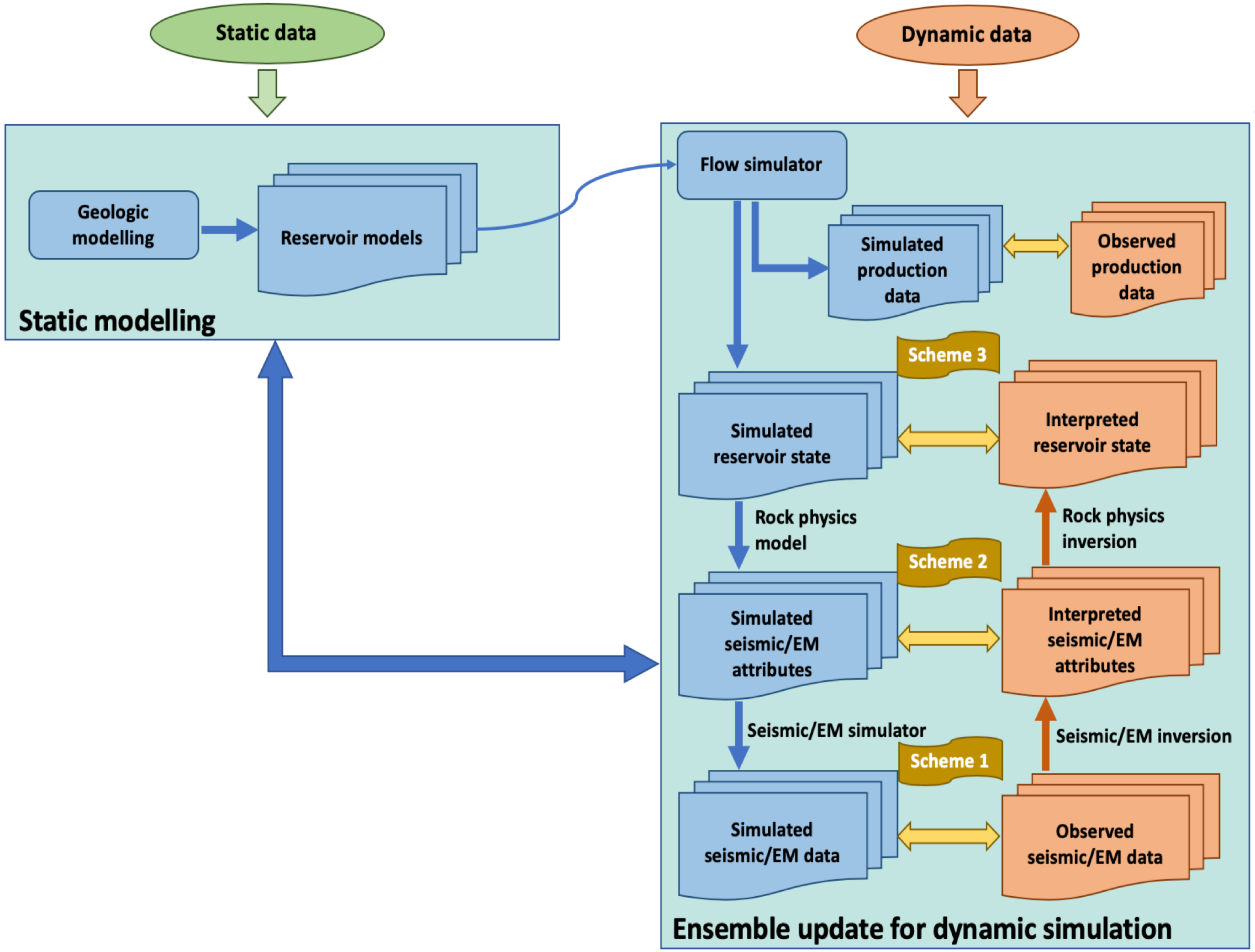
About the presenter

Yanhui Zhang is currently a postdoctoral researcher in the Physical Science and Engineering Division at King Abdullah University of Science and Technology (KAUST), Saudi Arabia. His research interests include reservoir history matching, dynamic data assimilation, uncertainty quantification, and optimization. Zhang holds a master's degree in petroleum engineering from Northeast Petroleum University, China, and a PhD degree in applied mathematics from the University of Bergen, Norway.

Outline

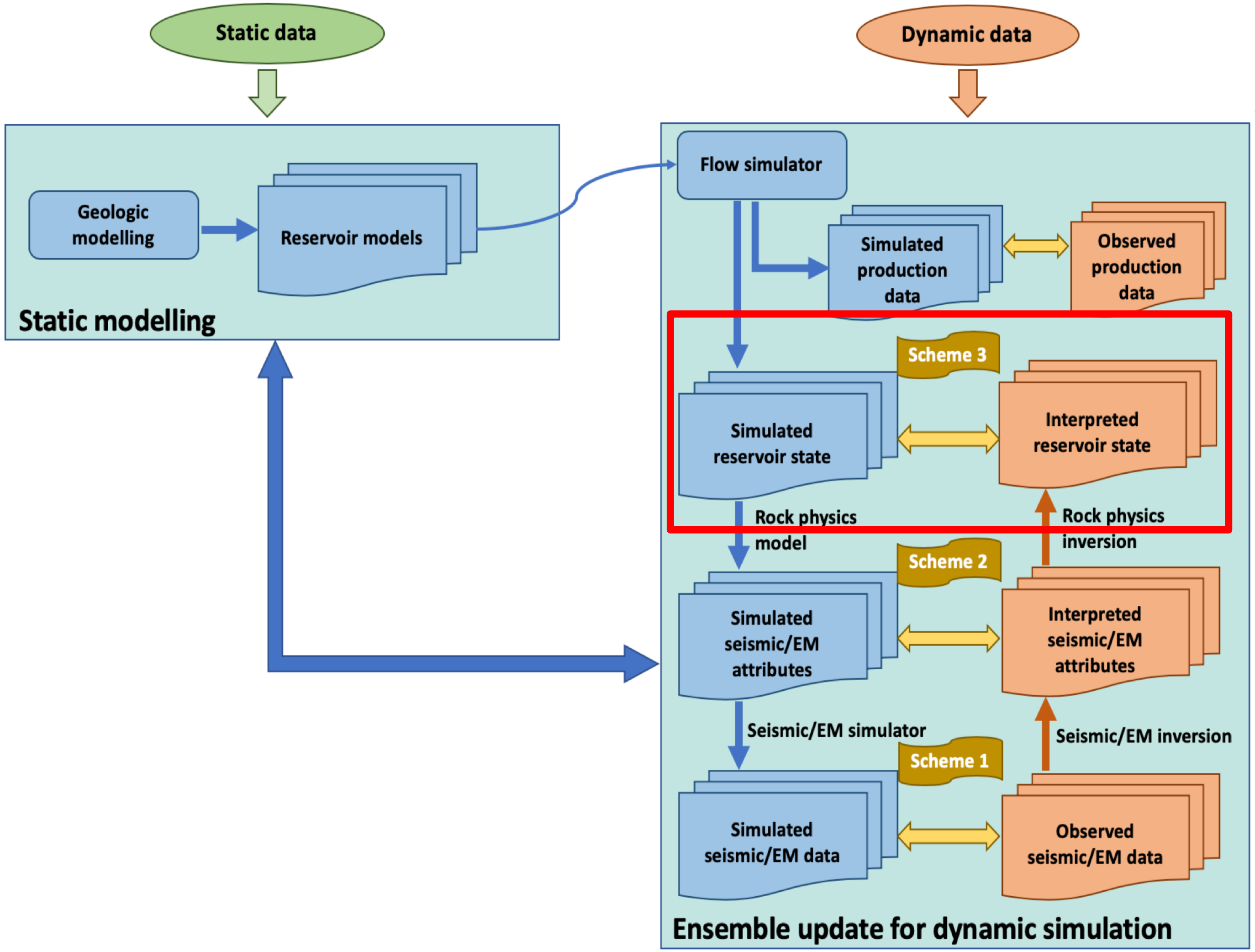
- Motivation
- Feature-oriented ensemble history-matching workflow
- Synthetic experiment with channelized reservoir model
- Conclusions

Motivation – history matching of geophysical data



- There exist different levels at which the associated forms of geophysical data can be integrated.
- Each level involves different degrees of forward modelling and inversion processes.

Motivation – history matching of geophysical data



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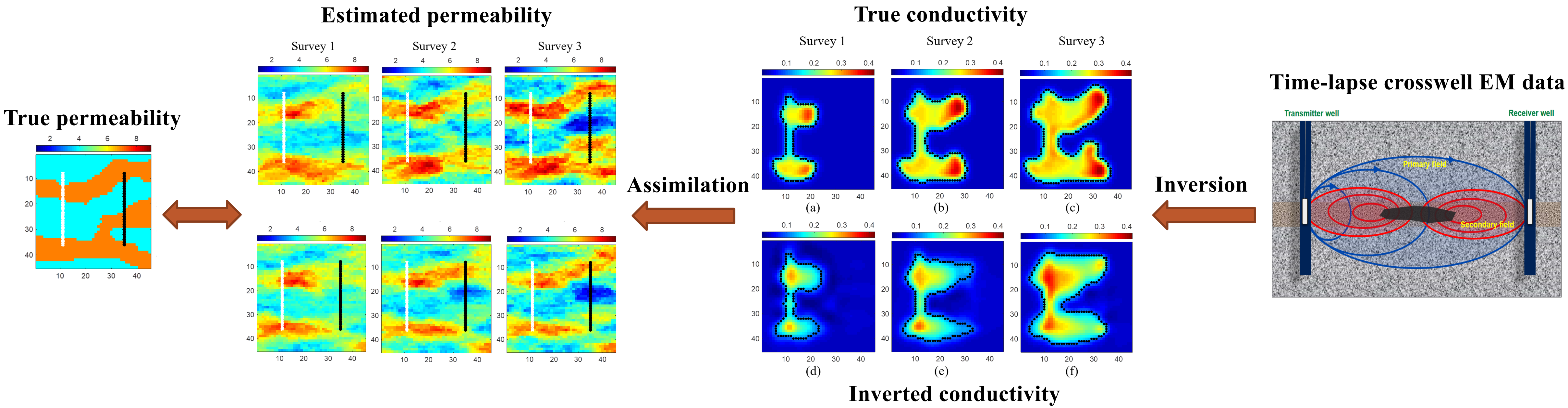
Motivation – feature-based approach + joint inversion

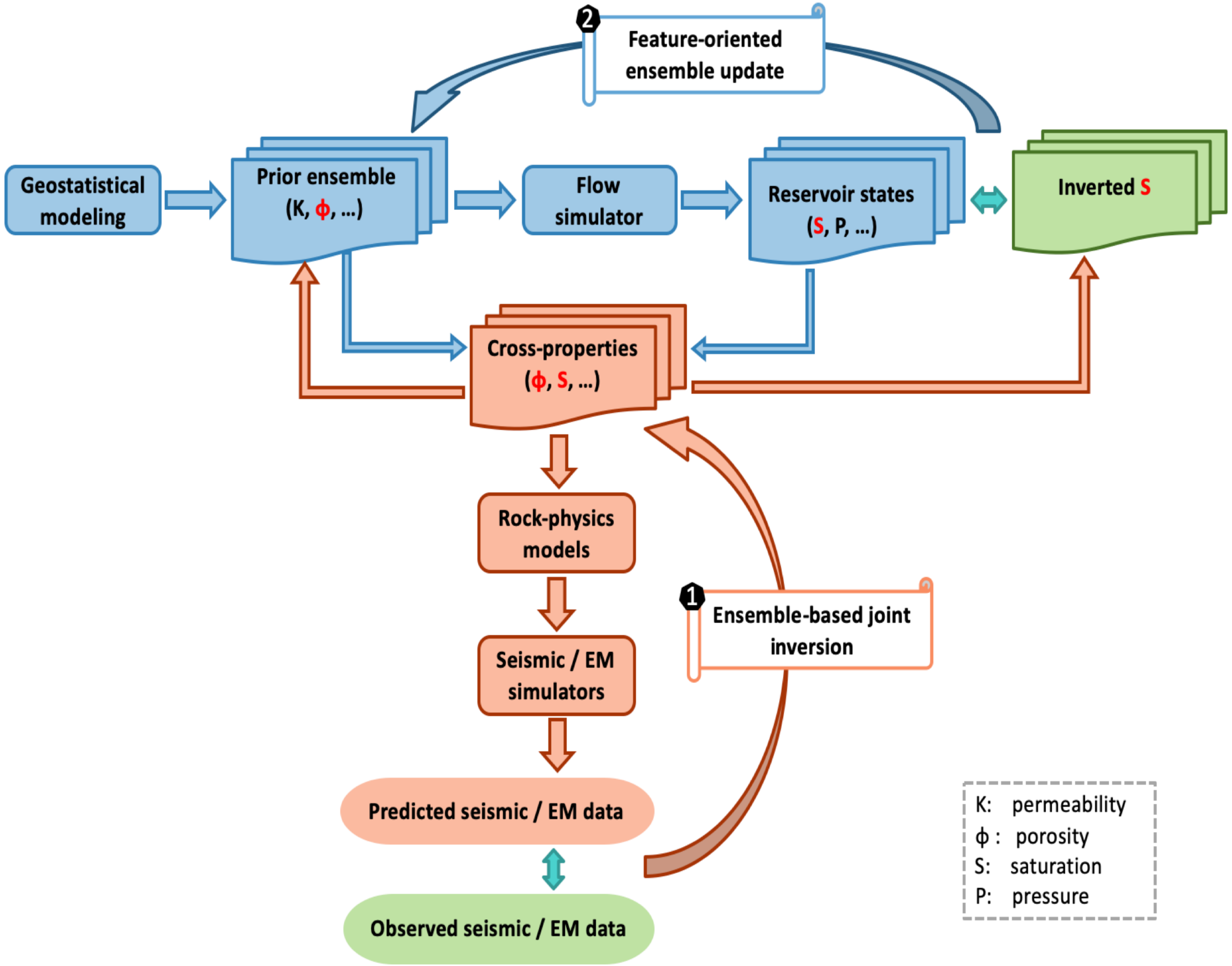
- Zhang et al. (2019)* showed that feature-based history-matching approach is promising but depends on the quality of geophysical inversion results.



- Joint inversion of multiple sources of geophysical data shows great potential to enhance the fidelity of inverted models.

** Zhang, Y. and Hoteit, I. 2019. Efficient Assimilation of Crosswell Electromagnetic Data Using Ensemble-Based History-Matching Framework.*

Feature-oriented ensemble history matching workflow



The developed workflow consists of two main steps:

- **Step one**: update rock cross-properties via joint seismic and electromagnetic (EM) inversion using ensemble methods.
- **Step two**: condition the rest reservoir properties of interest upon the updated cross-properties via feature-based assimilation approach.

Iterative ensemble smoother

- LM-EnRML (*Chen and Oliver, 2013*)*:

$$\mathbf{O}_{\mathrm{i}}(\mathrm{m}) = \overbrace{\frac{1}{2}\left(\mathbf{m} - \mathbf{m}_{\mathrm{i}}^{\mathrm{pr}}\right)^{\mathrm{T}} \mathbf{C}_{\mathrm{M}}^{-1}\left(\mathbf{m} - \mathbf{m}_{\mathrm{i}}^{\mathrm{pr}}\right)}^{\textbf{Model mismatch term}} + \overbrace{\frac{1}{2}\left(\mathbf{g}(\mathbf{m}) - \mathbf{d}_{\mathrm{obs,i}}\right)^{\mathrm{T}} \mathbf{C}_{\mathrm{D}}^{-1}\left(\mathbf{g}(\mathbf{m}) - \mathbf{d}_{\mathrm{obs,i}}\right)}^{\textbf{Data mismatch term}}$$

At ℓth iteration:

$$\delta\mathbf{m}_{\mathrm{i}}^{\ell} = \underbrace{\Delta\mathbf{M}^{\ell}\Delta\mathbf{D}^{\ell\mathrm{T}}\left[(1+\lambda_{\ell})\mathbf{I}_{\mathrm{N_d}} + \Delta\mathbf{D}^{\ell}\Delta\mathbf{D}^{\ell\mathrm{T}}\right]^{-1}}_{\textbf{Kalman gain}} \underbrace{\mathbf{C}_{\mathrm{D}}^{-\frac{1}{2}}\left(\mathbf{d}_{\mathrm{obs,i}} - \mathbf{g}\left(\mathbf{m}_{\mathrm{i}}^{\ell}\right)\right)}_{\textbf{Innovation}}$$

where $\Delta\mathbf{D}^{\ell} = \frac{\mathbf{C}_{\mathrm{D}}^{-\frac{1}{2}}\left(\mathbf{D}^{\ell} - \overline{\mathbf{D}^{\ell}}\right)}{\sqrt{\mathrm{N_e}-1}}$, $\Delta\mathbf{M}^{\ell} = \frac{\mathbf{M}^{\ell} - \overline{\mathbf{M}^{\ell}}}{\sqrt{\mathrm{N_e}-1}}$

* *Chen, Y. and Oliver, D.S. 2013. Levenberg-Marquardt forms of the iterative ensemble smoother for efficient history matching and uncertainty quantification.*

Kalman gain localization

- Kalman gain localization by bootstrap sampling (*Zhang and Oliver, 2010*)*:

$$\mathbf{K}^{loc} = \mathbf{L} \circ \left\{ \Delta\mathbf{M}^{\ell} \Delta\mathbf{D}^{\ell\mathrm{T}} \left[(1+\lambda_{\ell}) \mathbf{I}_{\mathrm{N}_d} + \Delta\mathbf{D}^{\ell} \Delta\mathbf{D}^{\ell\mathrm{T}} \right]^{-1} \right\}$$

where

$$\mathbf{L}_{ij} = \frac{1}{1 + \mathbf{R}_{ij}^2 (1 + 1/\gamma^2)},$$

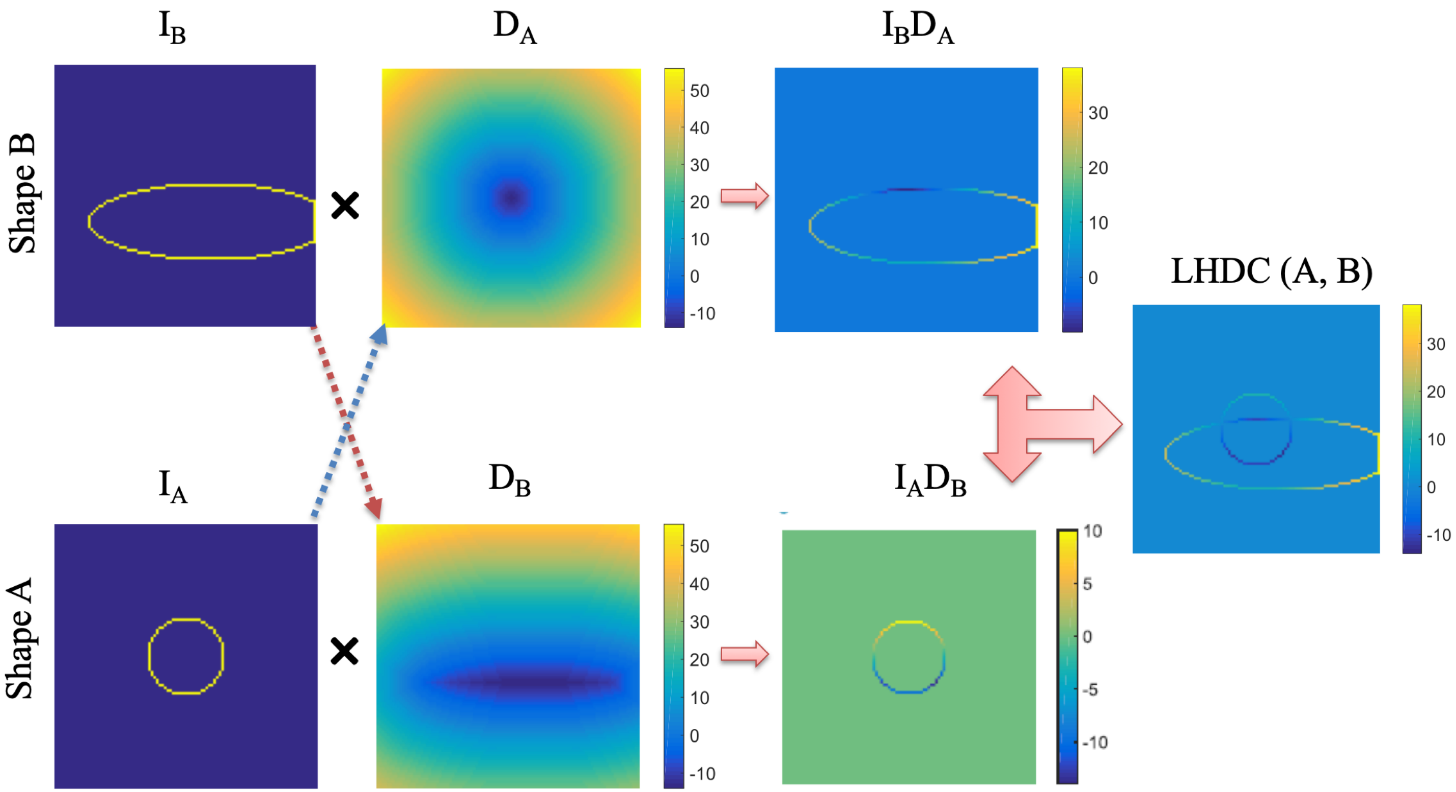
$$\mathbf{R}_{ij}^{\mathbf{2}} = \frac{\frac{1}{\mathrm{N}_b} \sum_{l=1}^{\mathrm{N}_b} (\mathbf{K}_{ij}^{l} - \mathbf{K}_{ij})^2}{\mathbf{K}_{ij}^2},$$

for $i = 1, 2, \ldots, \mathrm{N}_m,\ j = 1, 2, \ldots, \mathrm{N}_d$.

** Zhang, Y. and Oliver, D.S. 2010. Improving the ensemble estimate of the Kalman gain by bootstrap sampling.*

Feature-oriented distance parameterization

- Instead of integrating the whole resistivity field directly, the positions of saturation fronts are extracted and assimilated using a distance parameterization method (*Zhang and Leeuwenburgh, 2017*)*:



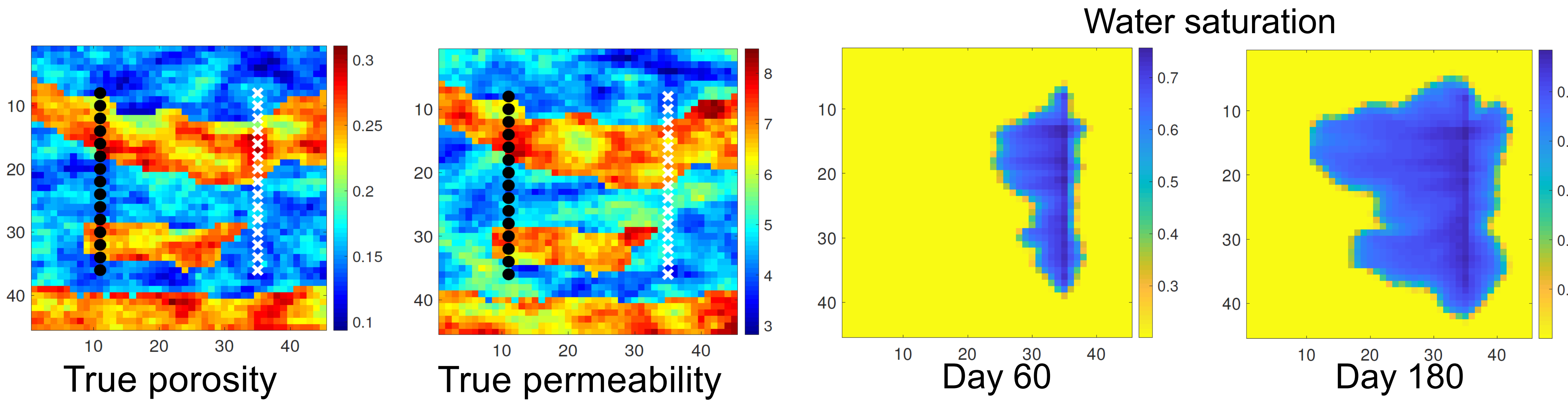
Local Hausdorff Distance with Contour (LHDC):

$$\mathrm{LHDC}(A, B) = \boldsymbol{I}_A \circ \boldsymbol{D}_B + \boldsymbol{I}_B \circ \boldsymbol{D}_A$$

* *Zhang, Y. and Leeuwenburgh, O. 2017. Image-oriented distance parameterization for ensemble-based seismic history matching.*

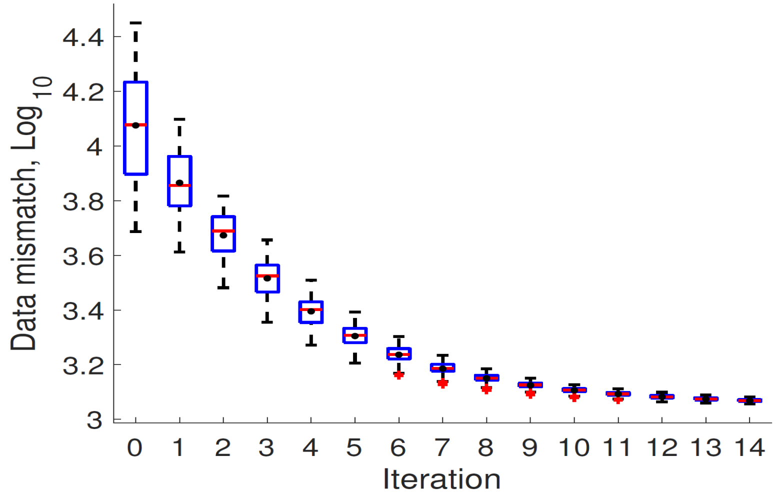
Example - synthetic channelized reservoir model

- Two facies types: channel sand and shale
- Fluid system: oil and brine
- Two horizontal wells: producer Bottom-Hole-Pressure (BHP) at 138 bar, injector rate at 200 sm^3/day
- Time-lapse crosswell seismic and EM surveys at day 60 and 180
- Uncertain parameters: porosity and permeability

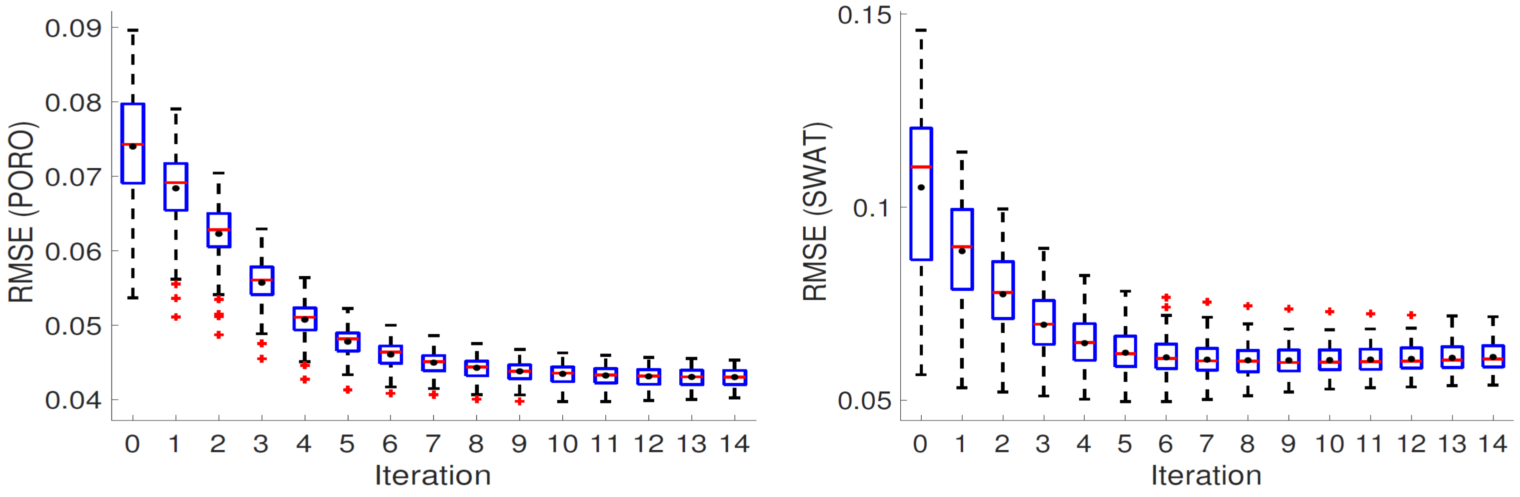


Results: day 60 - step 1

- Both data mismatch and Root-Mean-Square Errors (RMSEs) of porosity and water saturation were consistently reduced along with iterations.



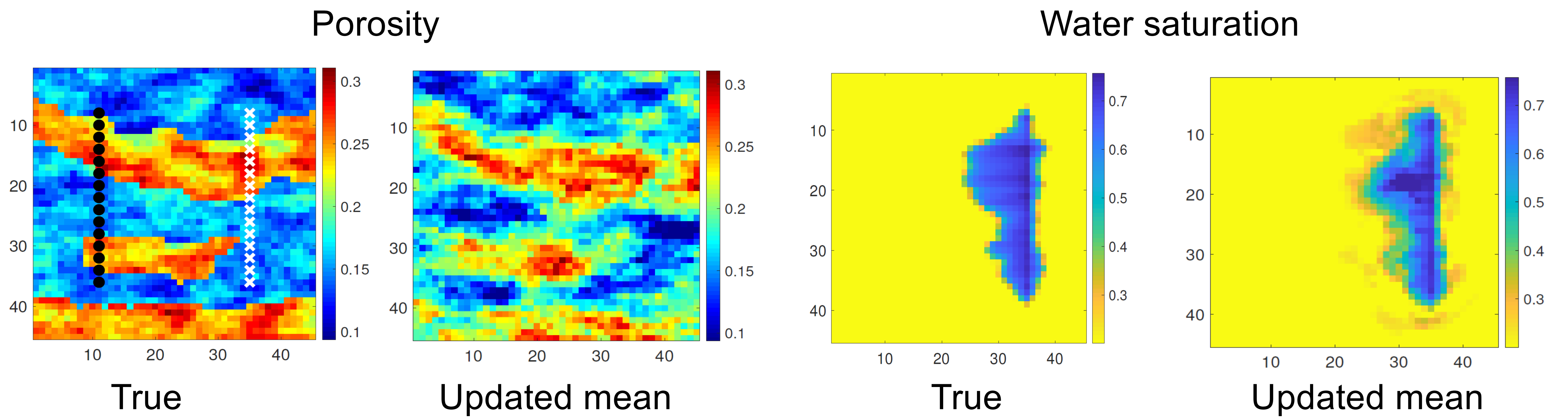
Data mismatch



RMSEs of porosity and water saturation

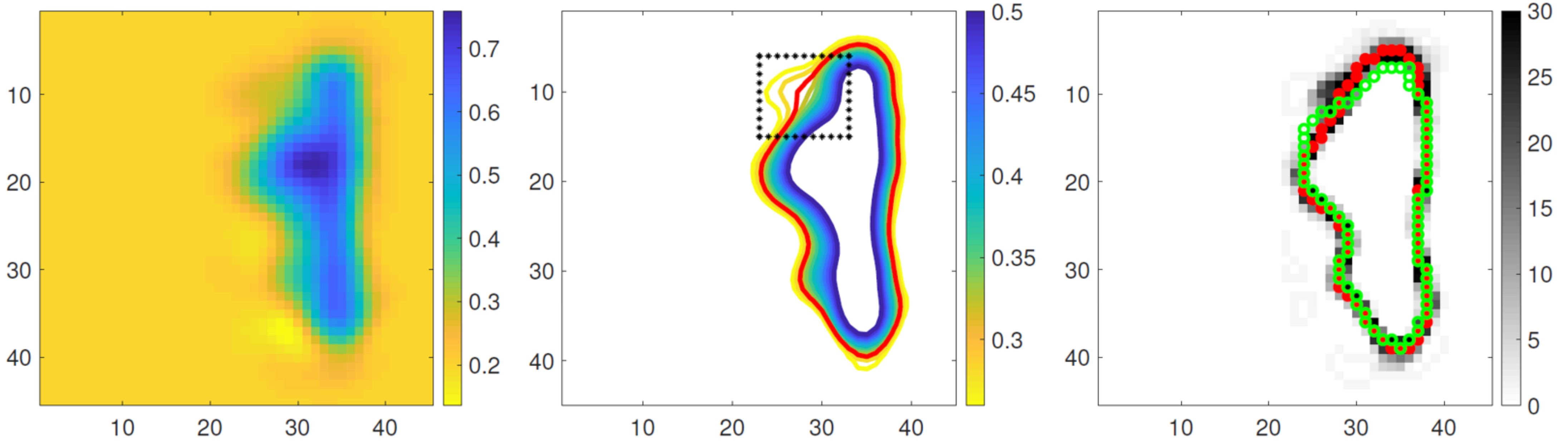
Results: day 60 - step 1

- Updated ensemble means of porosity and water saturation fields reproduced the main features observed in the corresponding true models.



Results: day 60 - step 2

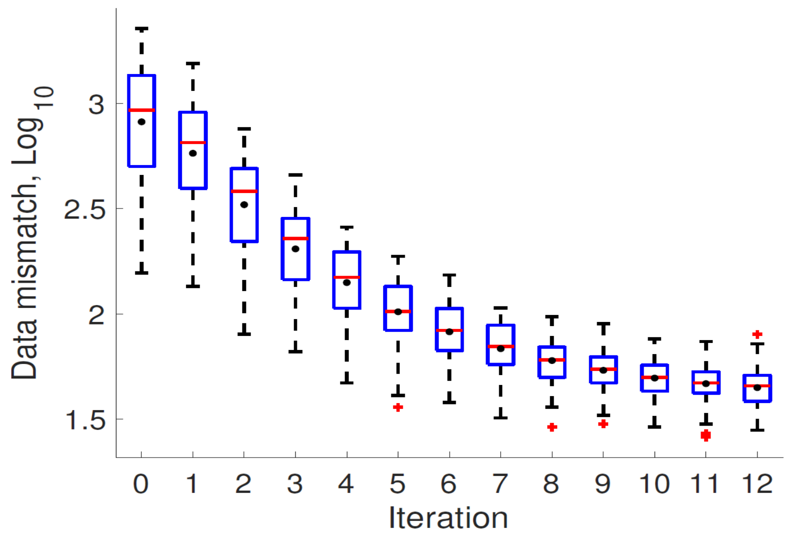
- Determination and extraction of saturation fronts from the inverted mean saturation field.



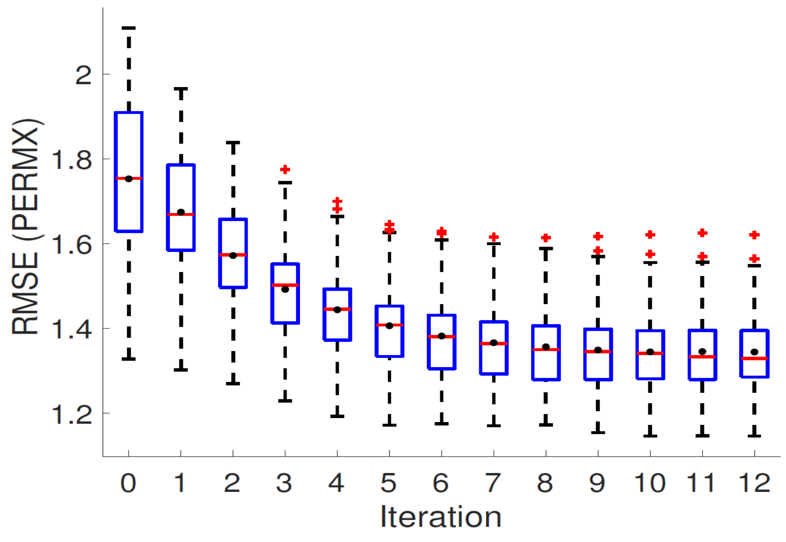
(a) Smoothed mean (b) Truncated contours (c) Extracted fronts

Results: day 60 - step 2

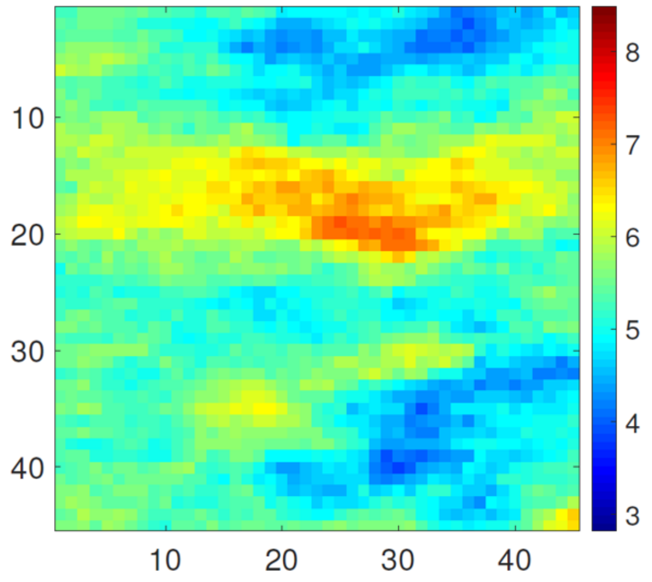
- Consistent reduction of data mismatch and the RMSE of permeability along with the iteration.



Data mismatch

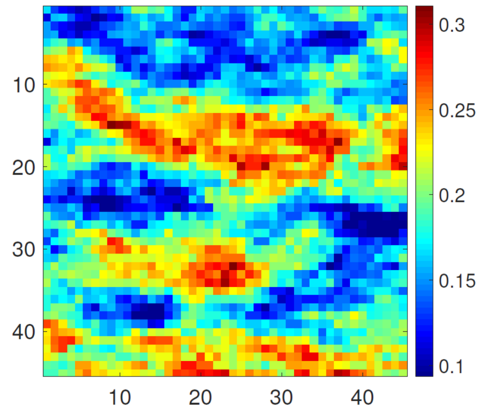


RMSE

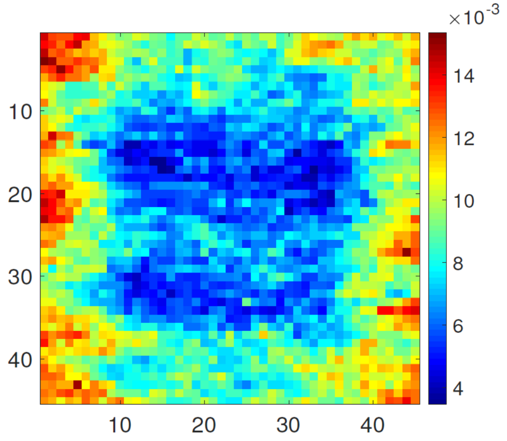


Updated mean

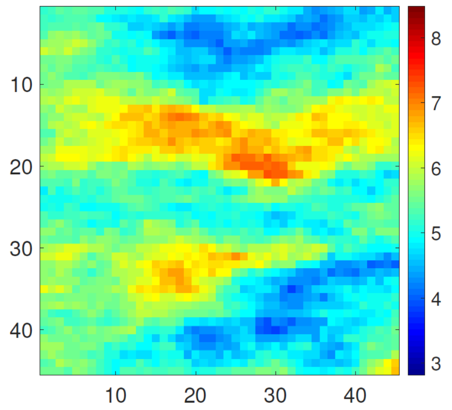
Results: day 180 - step 2



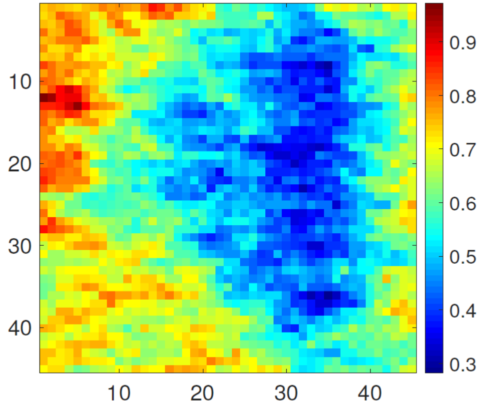
Mean - poro



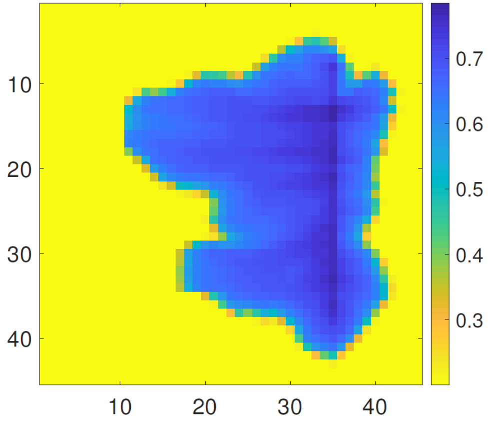
Standard deviation (STD)



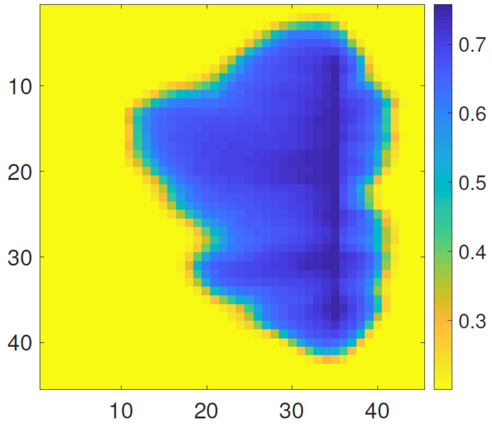
Mean - perm



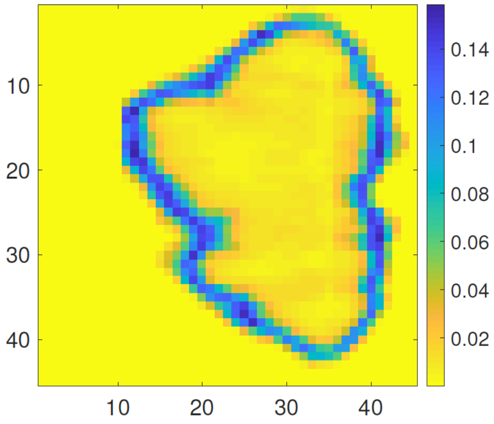
STD



True saturation



Predicted mean



STD

Conclusions

- A feature-oriented ensemble history-matching workflow is introduced with a focus on the joint assimilation of time-lapse seismic and EM data.

- Experiment results demonstrated that the developed workflow provides a novel and effective way to incorporate the information from multiple sources of geophysical data into reservoir models.

- More details can be found in published paper '*Feature-Oriented Joint Time-Lapse Seismic and Electromagnetic History Matching Using Ensemble Methods*' (SPE-203847-PA).

Acknowledgements / Thank You / Questions

- The study is supported by the research project "*Efficient Integration of Electromagnetic Tomography into Reservoir History Matching*" which is funded by Saudi Aramco.