Spatio-temporal tools in low complexity modelling of oil reservoirs

Edwin Insuasty, Paul Van den Hof,
Siep Weiland, Jan Dirk Jansen

10 November 2016, ISAPP Symposium, Delft

TU Delft

TU/e Technische Universiteit Eindhoven University of Technology

Where innovation starts

Introduction

- Reservoir models used in model-based operational strategies are generally too complex

Two aspects:

- Dynamic complexity (state space dimension induced by grid)
- Structural complexity
  (details of permeability patterns, parametrization of models)

Importance:

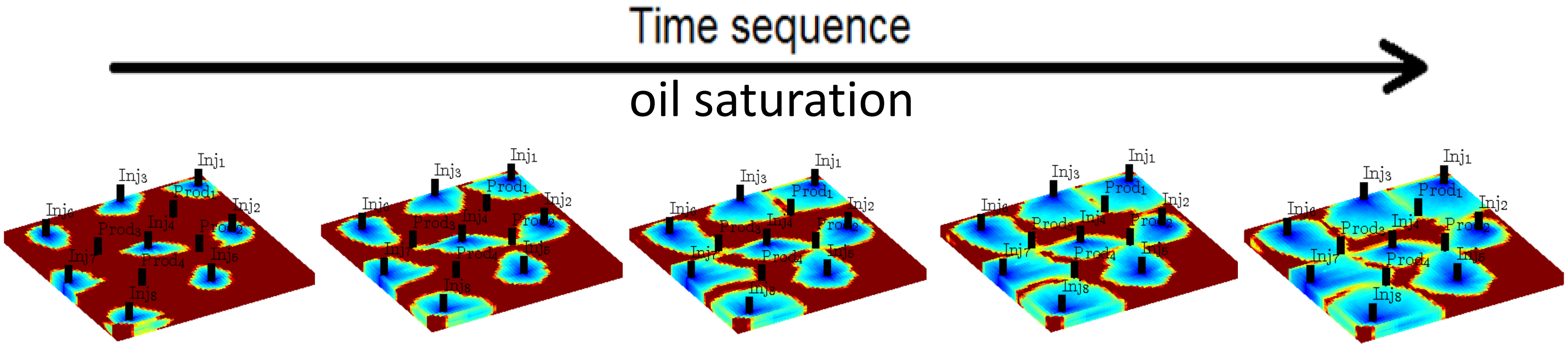
Dynamic complexity (state space dimension induced by grid)

- Computational complexity
- How to simplify models while keeping the major properties?
- What are appropriate dissimilarity measures between models?
- Both for model reduction and for model clustering (robust optimization)

Structural complexity
(details of permeability patterns, parametrization of models)

- Impossible to validate from data (lack of identifiability)
- Hard to assimilate data in a correct way into the models
- Highly dependent on priors

Reservoir models: when are they similar?



Reservoirs have structure!... Towards a better understanding of spatial-temporal correlations

Low dimensional representation of flow-behaviour (saturations):

$$\mathcal{S} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} \sigma_{ijk}\,\varphi_i \otimes \psi_j \otimes \chi_k = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} \sigma_{ijk}\Theta_{ijk},$$

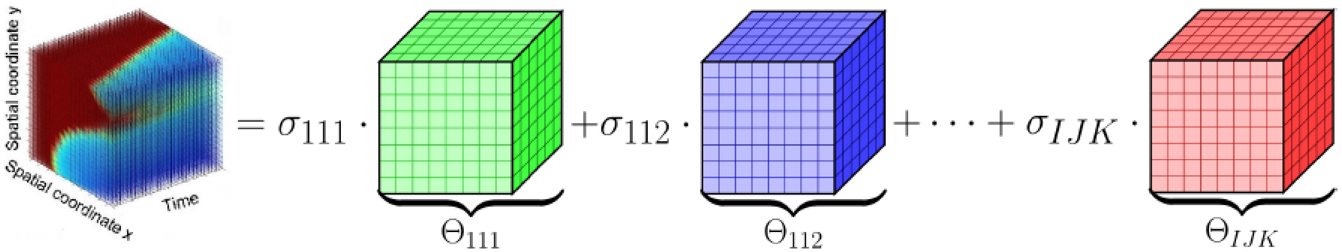
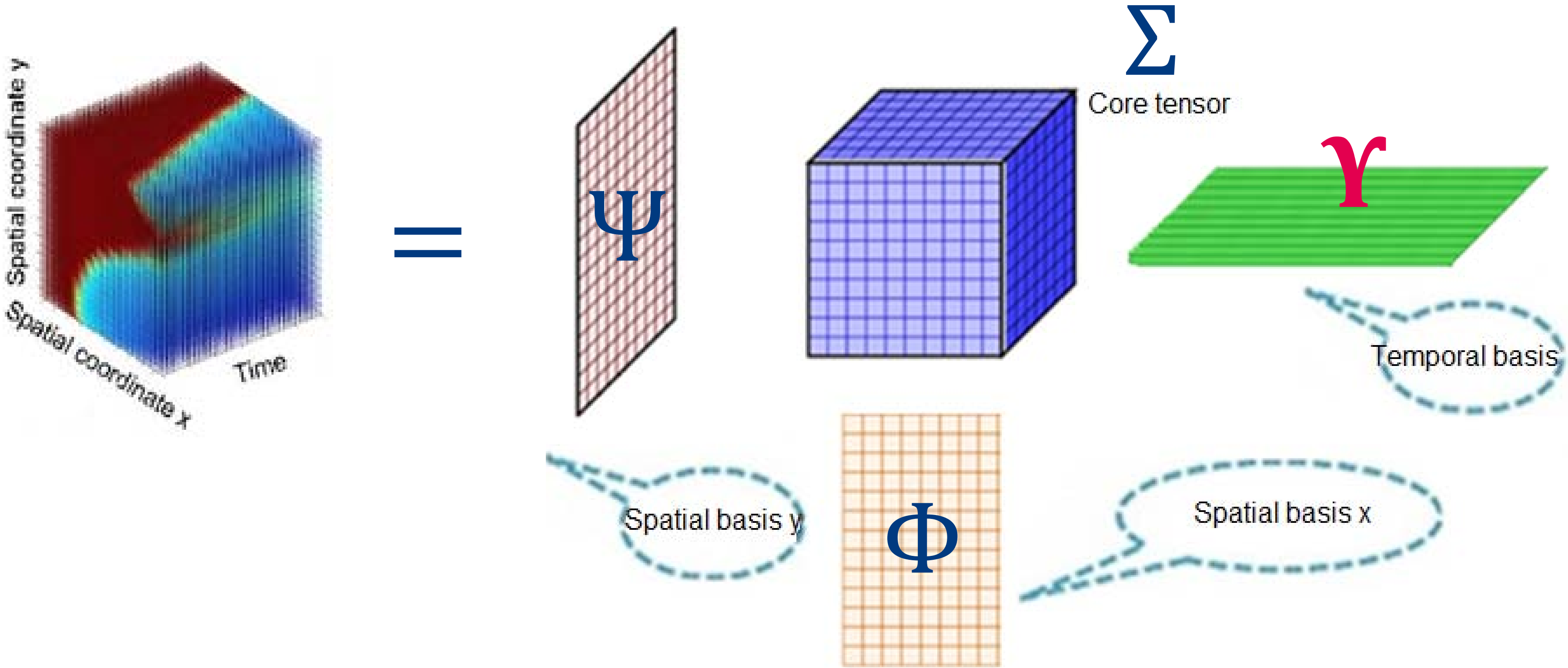


Figure 2: Schematic description for the truncation of a Tucker decomposition of a 3D tensor.

$$\widehat{\mathcal{S}} := \sum_{i=1}^{\widehat{I}}\sum_{j=1}^{\widehat{J}}\sum_{k=1}^{\widehat{K}} \sigma_{ijk}\Theta_{ijk}$$

Tensor decompositions



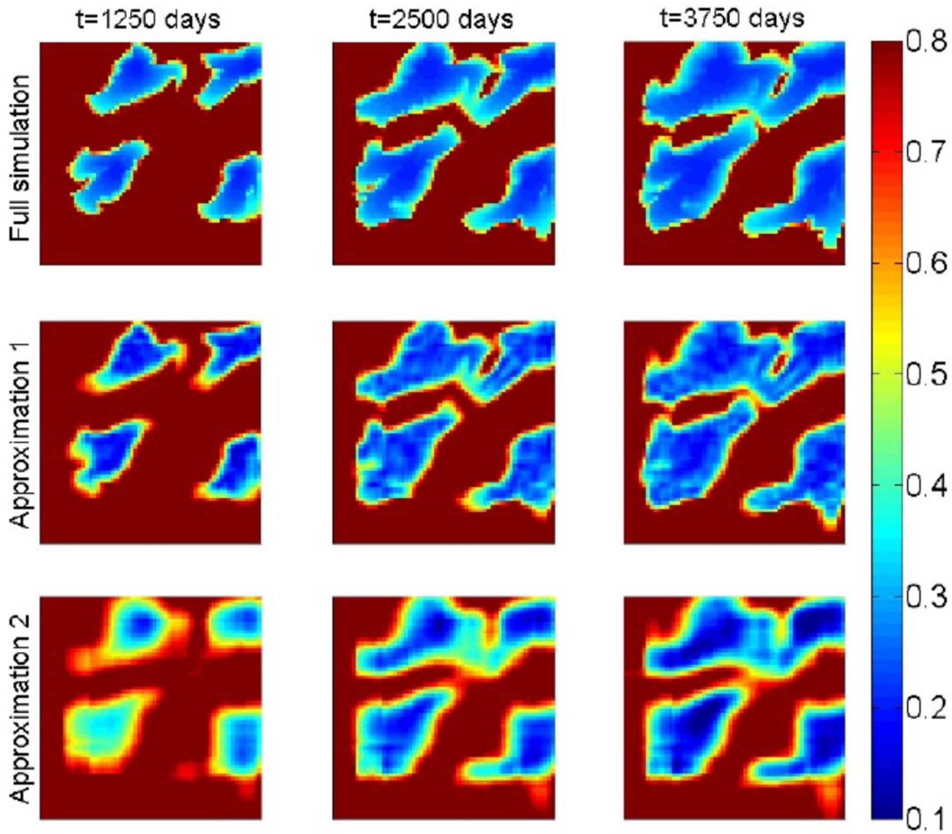
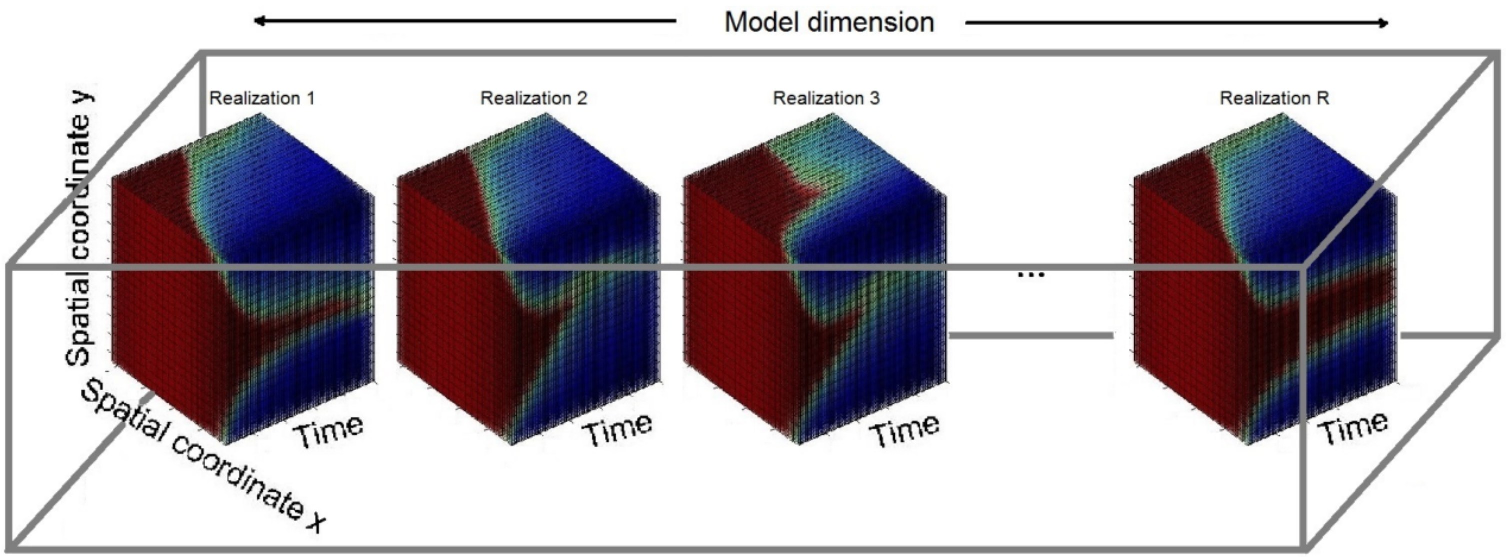


Figure 3: Oil-water front with tensor approximations. Approximation 1 has modal rank (20, 20, 5). Approximation 2 has modal rank (10, 10, 5). Colors represent oil saturation.

60 x 60 grid blocks
1095 time steps

A tensor representation for multiple realizations

- 4D tensor
- To be used for calculation for model dissimilarity, and clustering

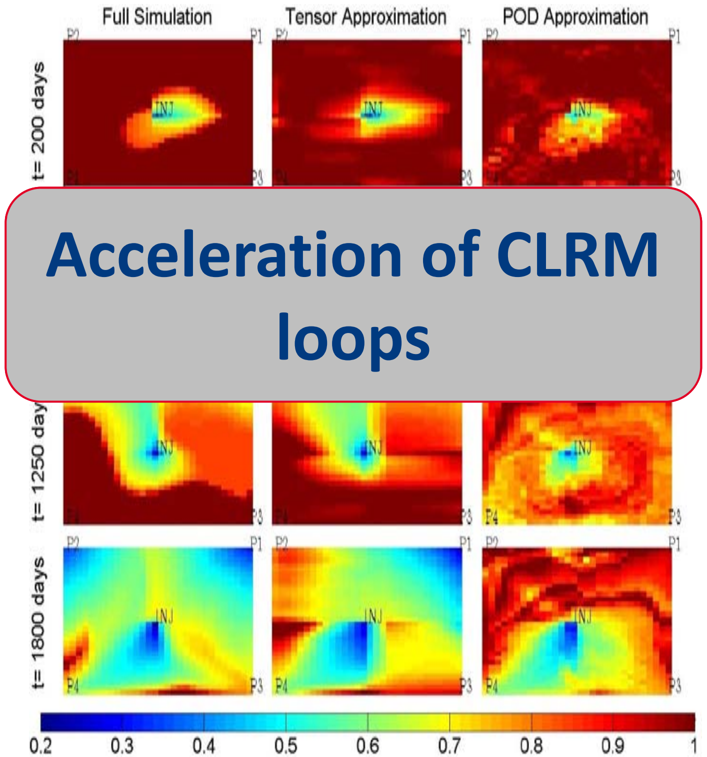


Properties of tensor analysis

- Keeps spatial structure intact (spatial-temporal correlations)
- Coordinate-independent analysis
- Huge compression rates (1~2 orders higher than SVD)
- Natural framework for data analysis in reservoir engineering.
- Visualization and computational time??

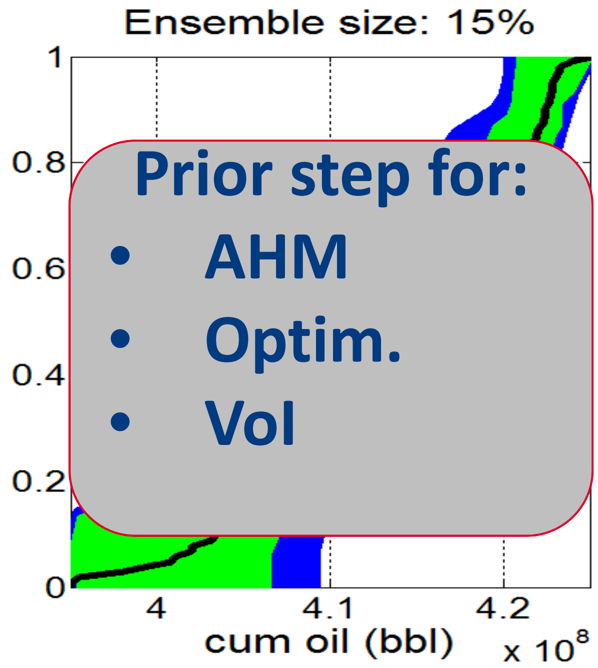
Phases: Tensor techniques for reservoir modeling

Tensor-based MOR



Acceleration of CLRM loops

Tensor-based flow characterization



Prior step for:

- AHM
- Optim.
- VoI

Green: Tensor Blue: Fingerprints[1]

[1]Yeh.T *et al. Reservoir Uncertainty Quantification Using Probabilistic History Matching Workflow*. SPE Annual Technical Conference and Exhibition, Amsterdam, 2014.

Tensor-based modeling of geological structures

Question?

Can we parametrize our reservoir models with a smaller number of parameters, but locating them in strategic positions, so as to be flexible to represent relevant and realistic reservoir models?

Parameterization of geology

Petrophysical properties

- Kernel methods, Sarma 2008, 2009
- O-PCA, Vo and Durlofsky 2015
- Cosine transforms, Jafarpour 2008

Facies

- MPS and parameterization of the facies pdf:

  Sabacher 2015. Hanea 2015.
- Set methods, Lorentzen 2012.

Objective

Exploit the structure and spatial correlations of the petrophysical properties to define a better representation of geological structures, identifiable from data .

METHOD

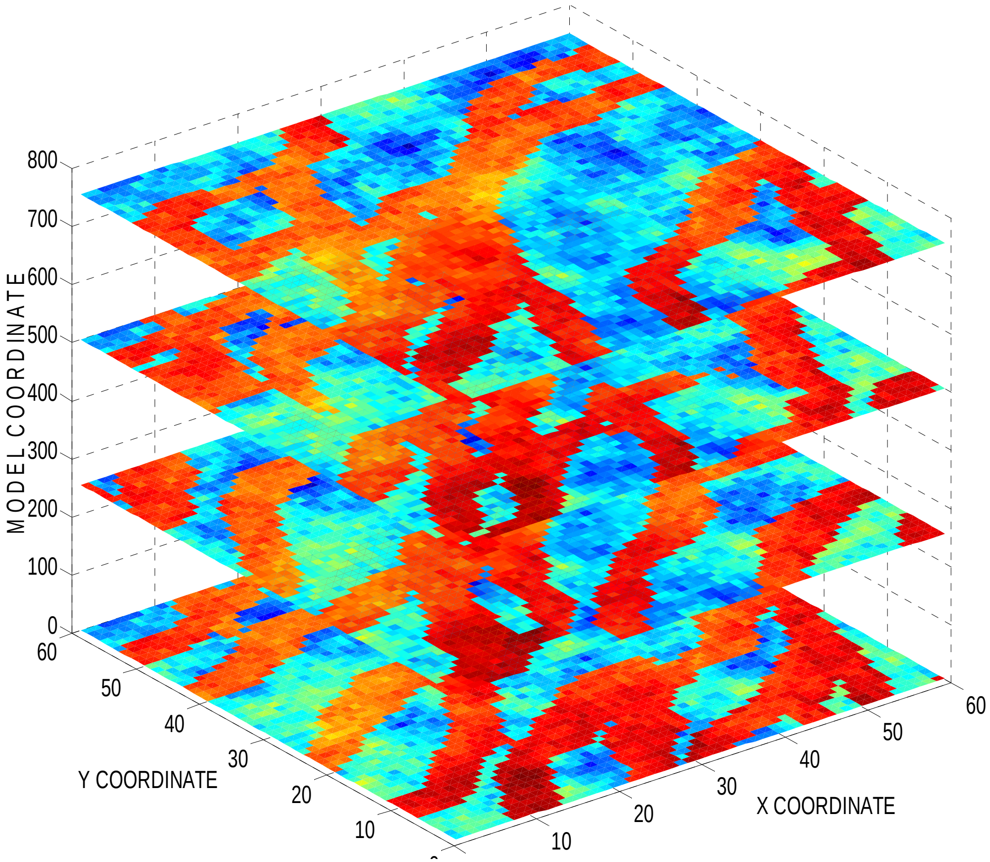
The development of a multilinear formulation for reduced-complexity geological models by extending the current PCA-based approaches to the case of multilinear analysis.

Extend the multilinear methods to:

PCA **Kernel PCA** **Optimization-based PCA**

Tensor representation of rock properties

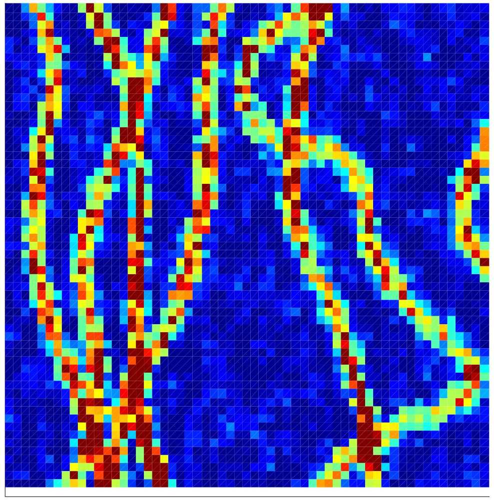
- Build a 3D (or 4D) tensor of *permeabilities* of an ensemble of (prior) models
- Select a reduced number of basis functions in each dimension
- Parametrize the model by fixing the basis functions and using the expansion coefficients as free parameters
- We keep structure intact.
- All dimensions are processed independently .



Low-rank approximation of rock properties

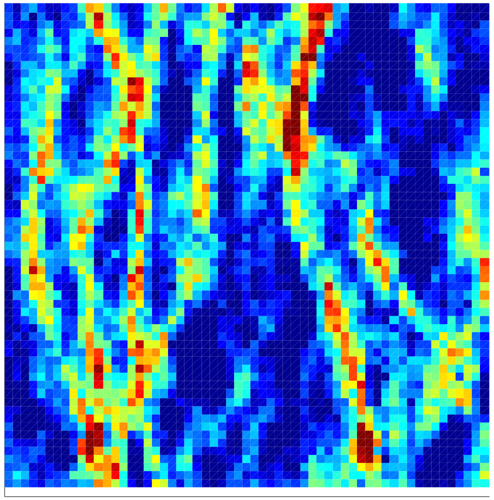
7 layers full data Egg model. 100 realizations of permeability.

Realization 3



20.16 MB

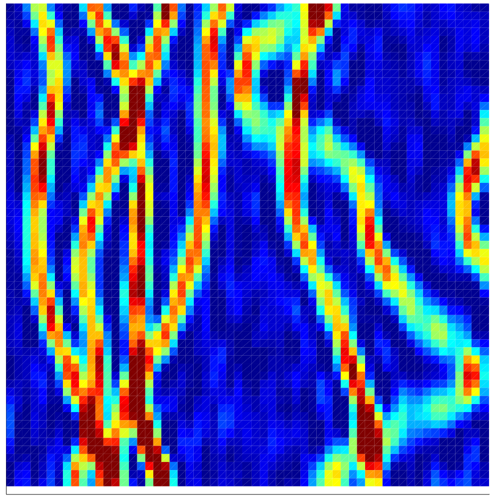
SVD approximation r=30



6.08 MB

30.1%

Tensor approximation
$\hat{I} = 15, \hat{J} = 35$



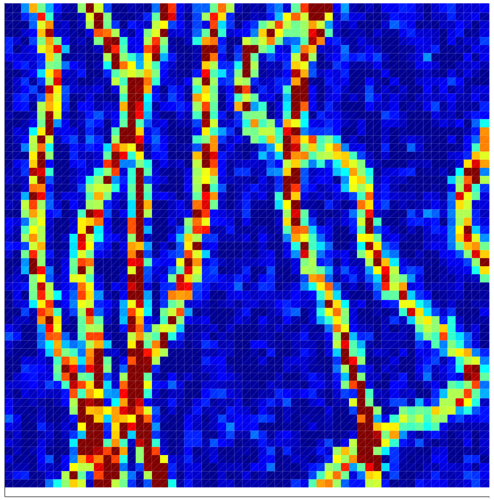
0.53 MB

2.6%

Low-rank approximation of rock properties

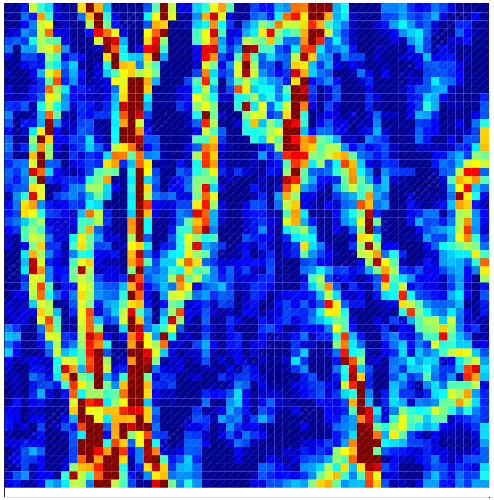
7 layers full data Egg model. 100 realizations of permeability.

Realization 3



20.16 MB

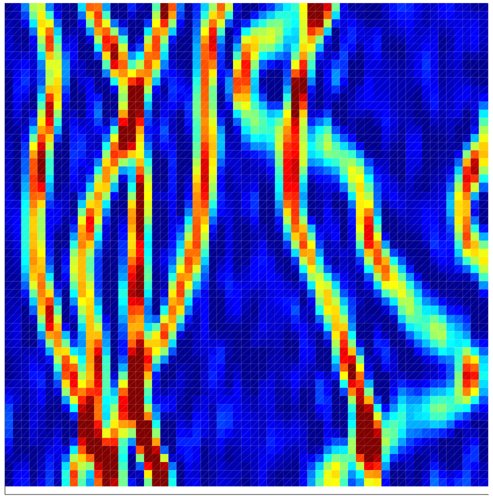
SVD approximation r=60



12.17 MB

60.3%

Tensor approximation
$\hat{I} = 15$, $\hat{J} = 35$



0.53 MB

2.6%

A tensor-based representation of rock properties (2D)

Tensor decomposition

$$X = \sum_{r}^{R} \sigma_r \cdot u_r \otimes v_r \otimes w_r$$

Representation of the m-th realization

$$\mathrm{x}_m = \sum_{r}^{R} \sigma_r \langle w_r, e_m \rangle \cdot u_r \otimes v_r$$

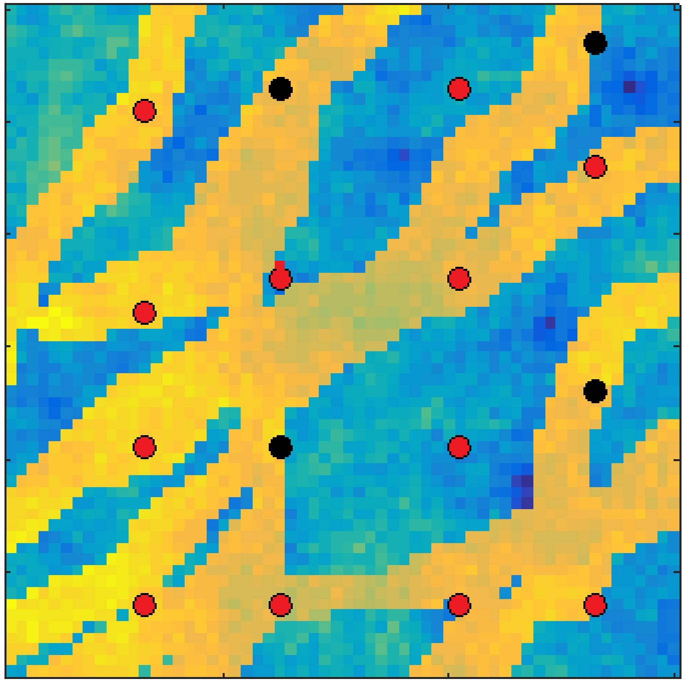
- The spatial basis tensors $u_r \otimes v_r$ are shared by all the realizations.
- The coefficients $\alpha_r = \sigma_r \langle w_r, e_m \rangle$ characterize each realization.
- Data-based estimation of R coefficients α_r

Technische Universiteit Eindhoven University of Technology

Estimating parameters through EnKF

- The prior models generate 100 prior parameter values α_r
- We extend the model states with the parameter α_r
- and jointly estimate states and parameters through EnKF

Experiment PCA vs Tensor estimation



Model:

- Stanford data set (3600 grid cells)
- Ensemble size: 100 realizations
- 12 prod, 4 inj

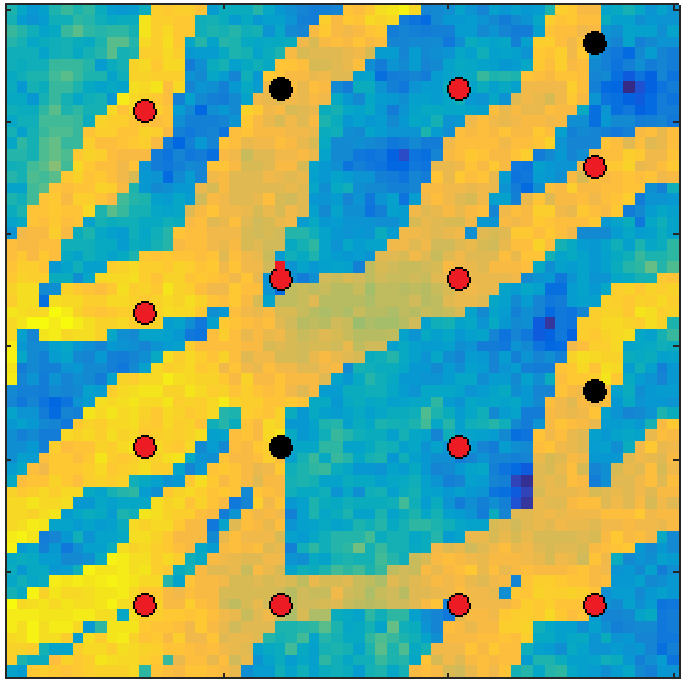
History matching exercise:

- Simulation time: 15 years
- Final update time: 6 year
- Update time interval: 2 year
- Measurement time interval: 3 month (rates and pressures)

Experiment PCA vs Tensor estimation

Model:

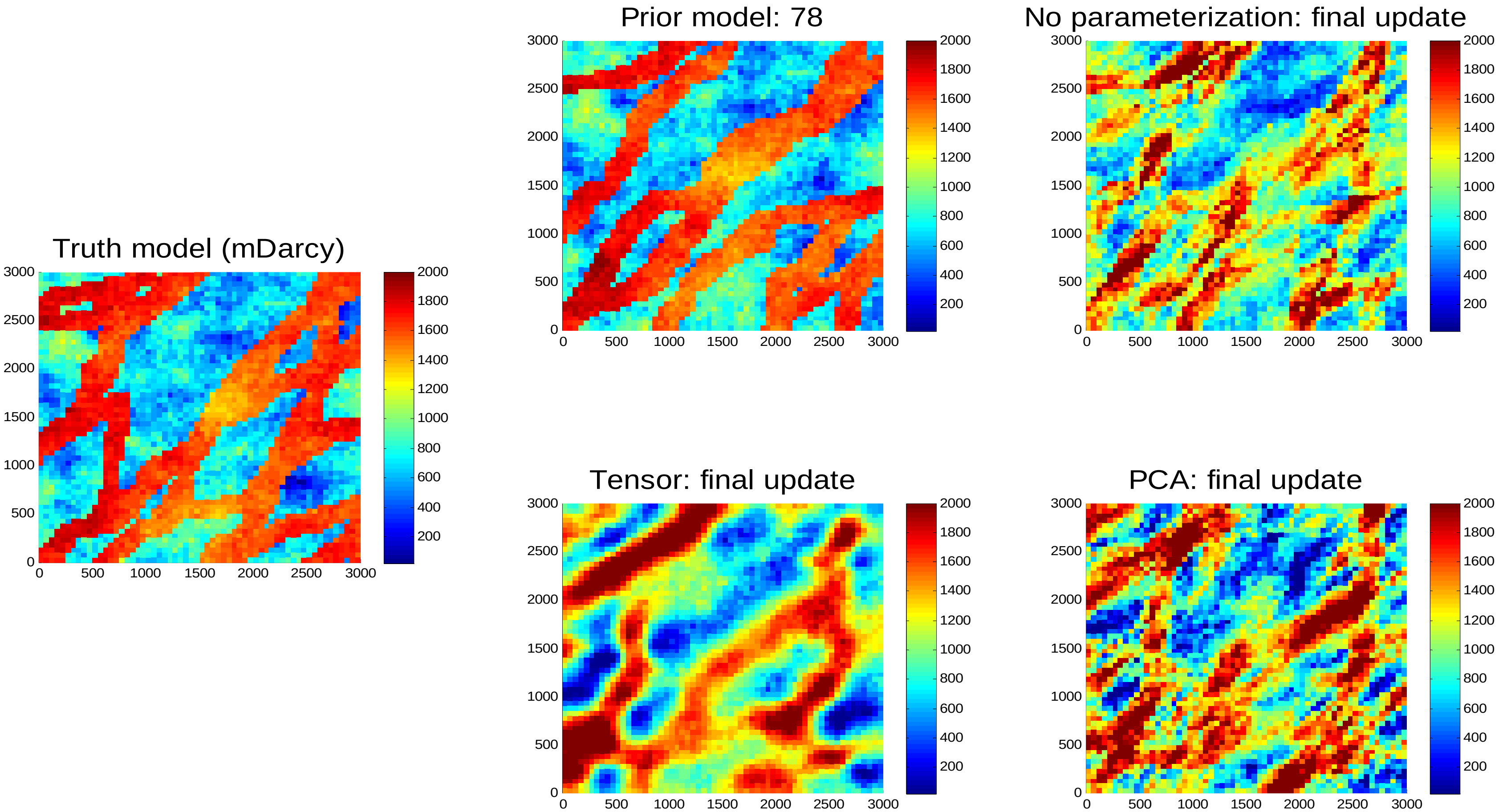
- Stanford data set (3600 grid cells)
- Ensemble size: 100 realizations
- 12 prod, 4 inj



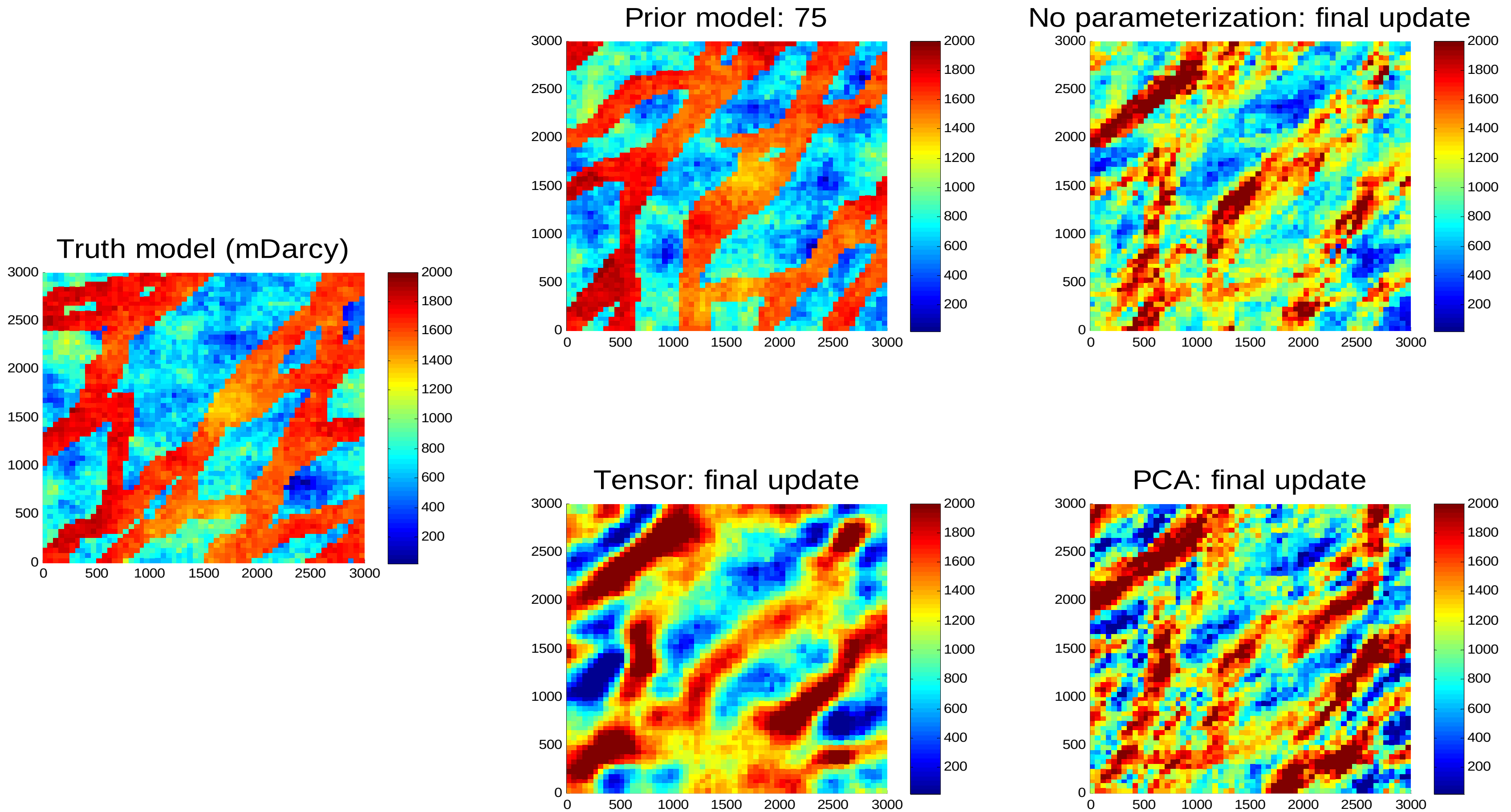
Representation

- Permeabilities
- PCA: 50 basis
- Tensor: 50 tensor basis

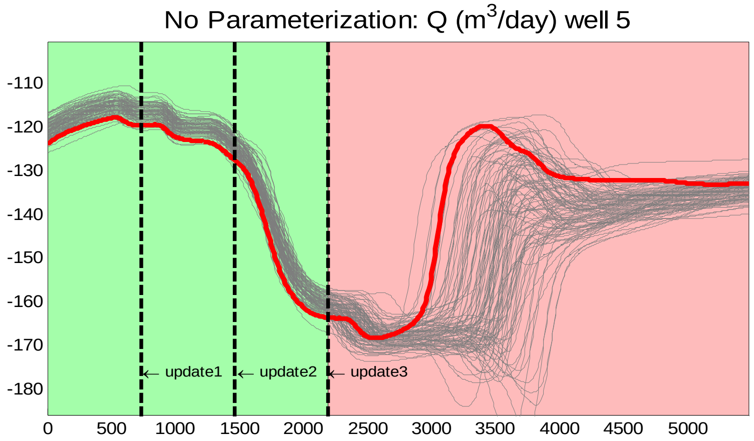
Model updates

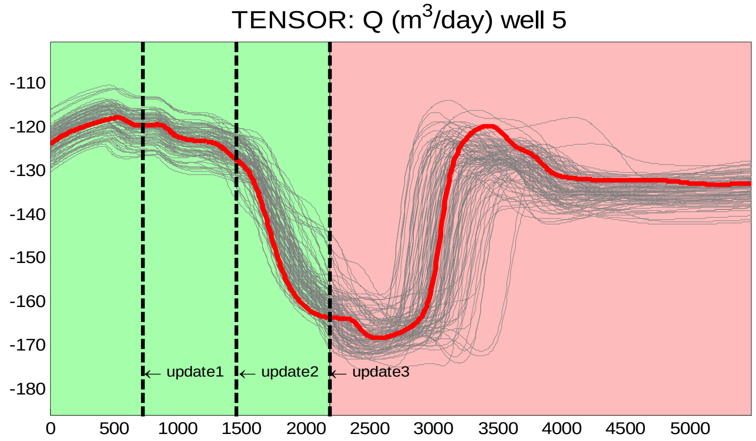


Model updates

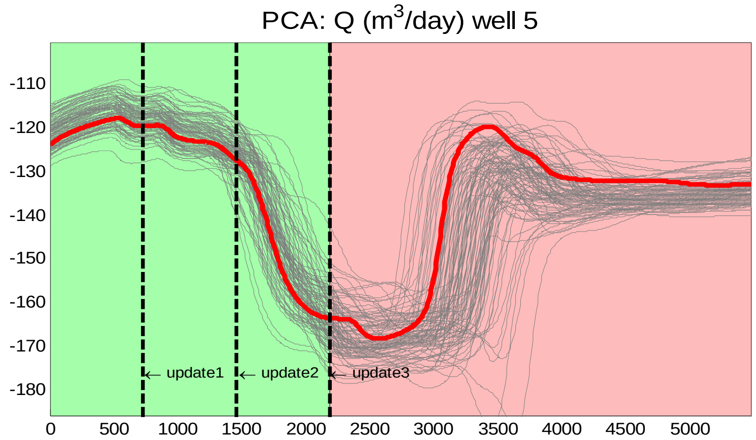


Total rates

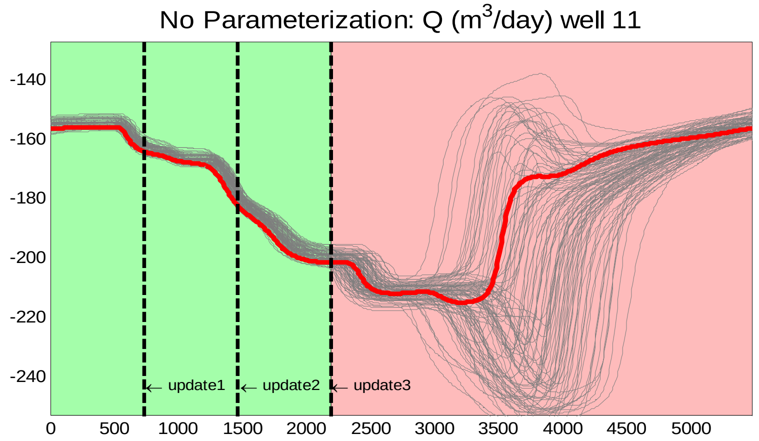


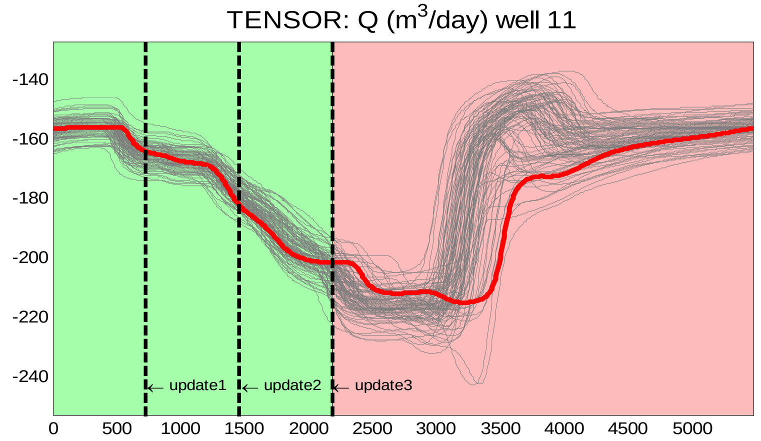


- HM with no param.: Good HM, Bad prediction.
- PCA: Fair HM, Fair prediction.
- Tensor: Fair HM, Good prediction

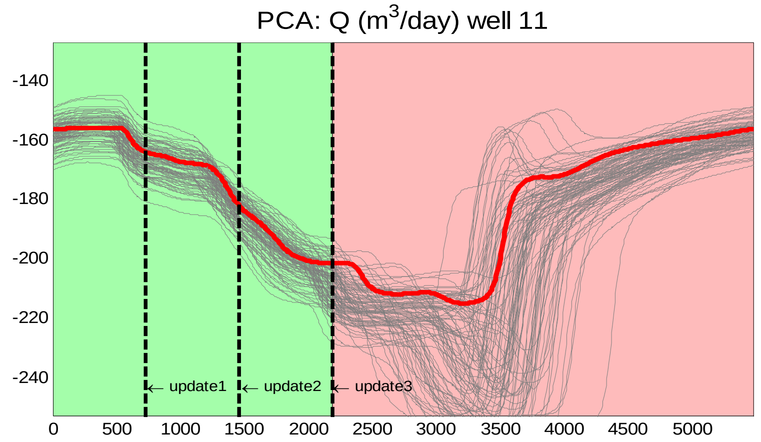


Total rates

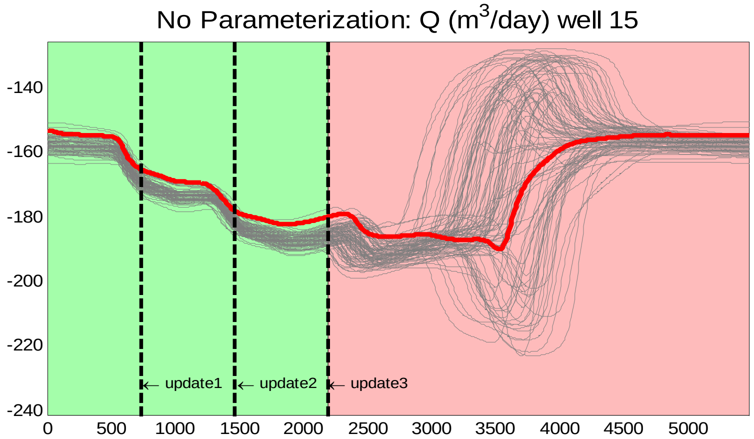


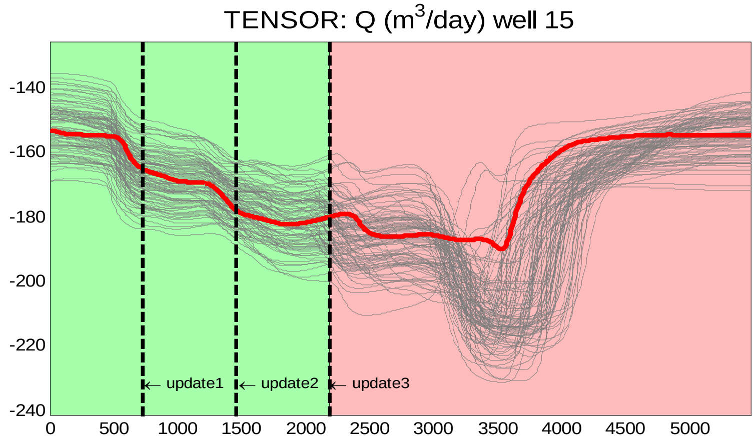


- HM with no param.: Good HM, Bad prediction.
- PCA: Fair HM, Bad prediction.
- Tensor: Fair HM, Fair prediction

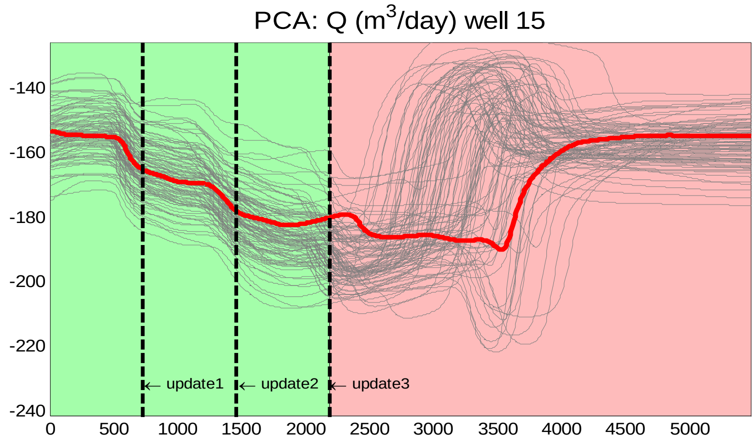


Total rates

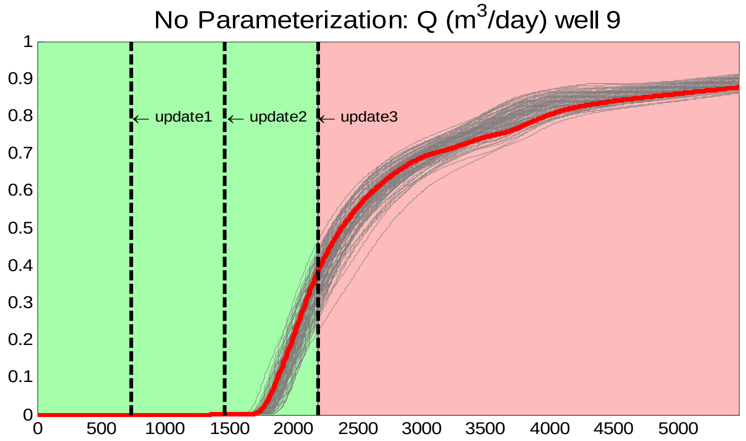


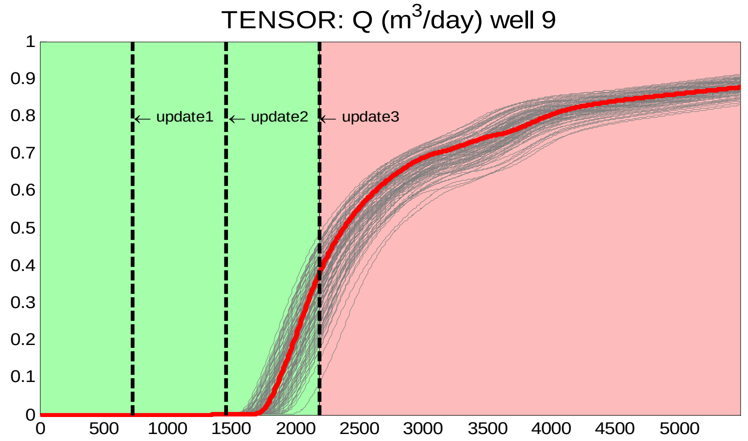


- HM with no param.: Good HM, Bad prediction.
- PCA: Fair HM, Bad prediction.
- Tensor: Fair HM, Fair prediction

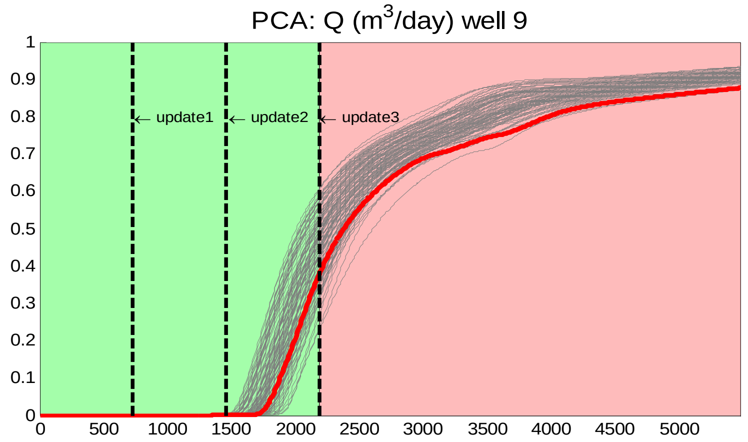


Fractional flow

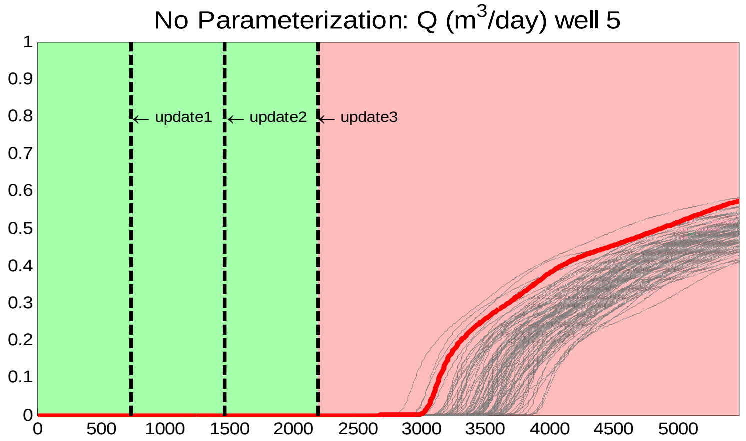


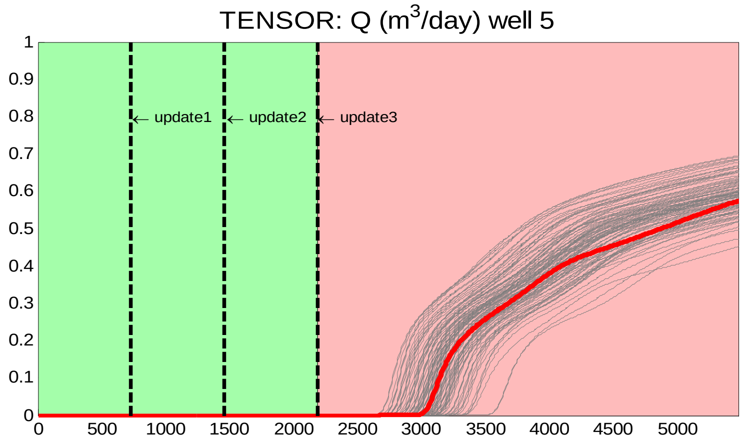


- Good HM for WCT before the end of HM.

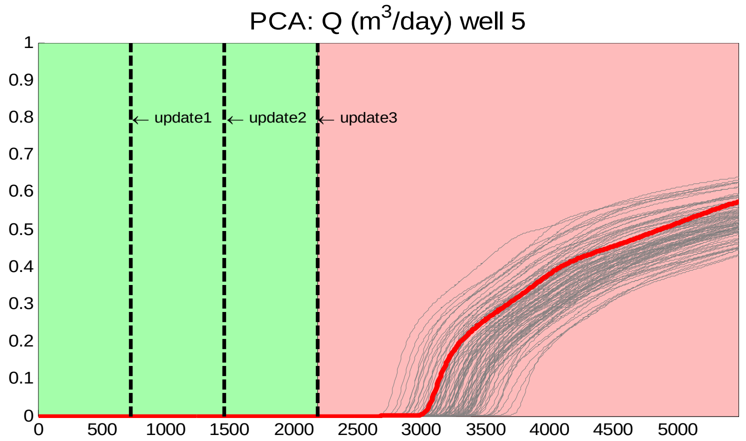


Fractional flow





- HM with no param.: Bad prediction.
- PCA: Fair prediction.
- Tensor: Good prediction



Conclusions

- Indication that the multilinear formulation and decomposition of geological structures captures efficiently spatial correlations of the rock properties.
- A decomposition comparable to the SVD (polyadic decomposition)
- Improved prediction capabilities of the updated models in HM.

E. Insuasty, “A spatio-temporal approach to reduced complexity modelling for hydrocarbon reservoir optimization”, PhD Thesis, 2017, to appear.

Acknowledgements / Thanks / Questions

The authors acknowledge financial support from the Recovery Factory program sponsored by Shell Global Solutions International.

Future

Spatio-temporal approach has good potentials, also i.t.o.optimization: which oil-water front scenarios are desirable/feasible?

Data-analytics and data-driven modelling (linear and nonlinear); sparse modelling

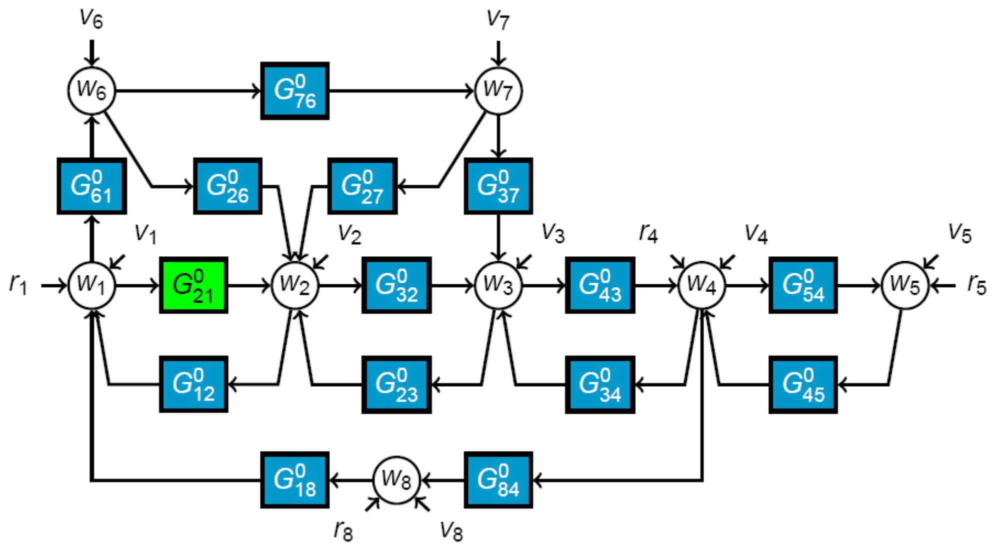
Data driven modelling in structured dynamic networks (e.g. in multi well testing)

Scenario-based model uncertainty

ERC Advanced Grant - SYSDYNET

Data-driven modelling in dynamic networks

European
Research
Council



1. Local identification (sensors, actuators, priors, experiment design, adapt)
2. Topology identification (local/global, non-directed graphs, priors)
3. Heterogeneous data (synchron, first principles, priors, communic)
4. Identification for distributed control
5. Software tools and applications