

DARTS workshop

Operator-Based Linearization approach:
general idea and implementation

Motivation

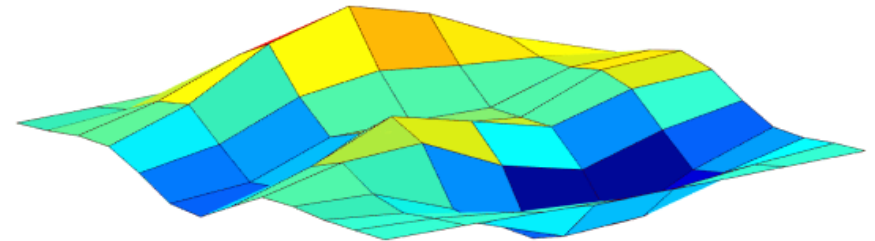
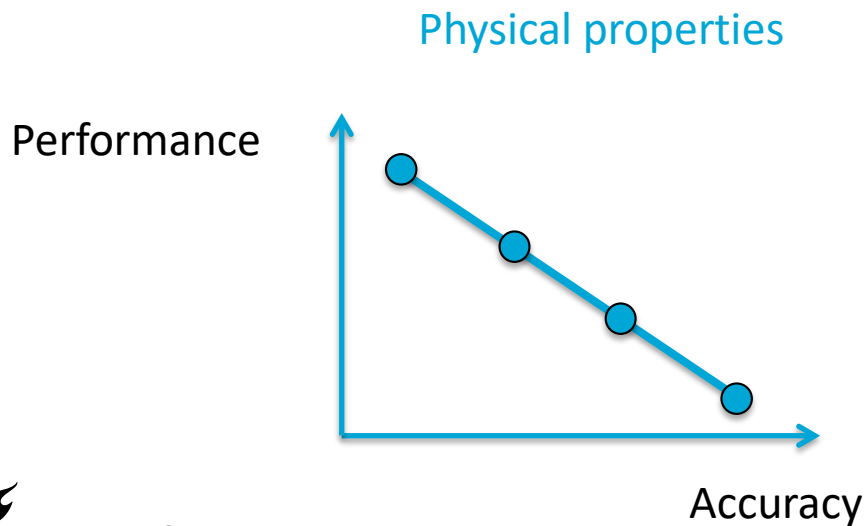
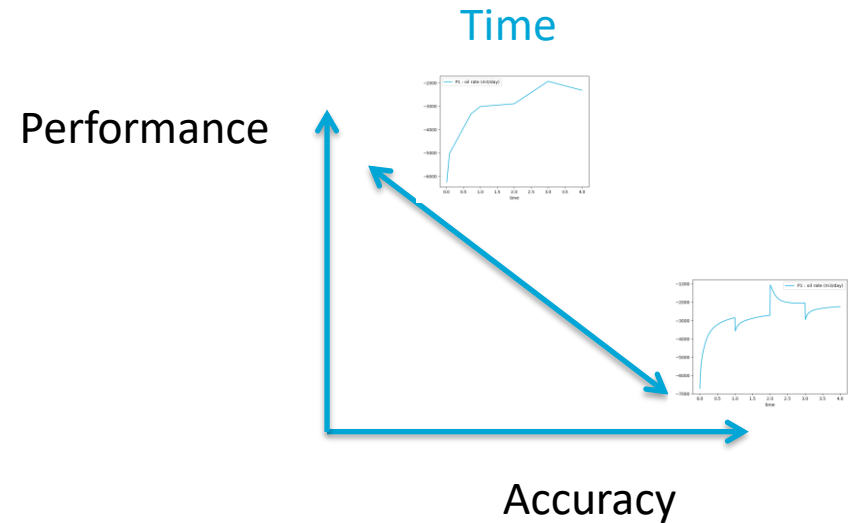
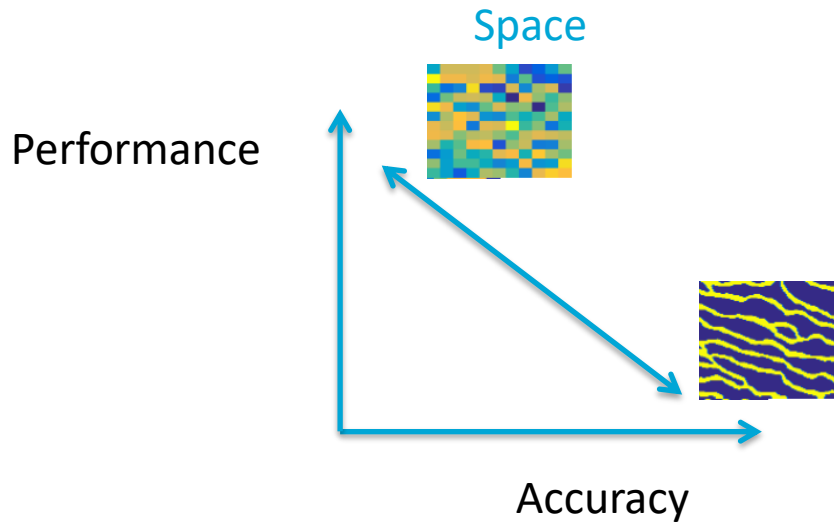
Increasing need for a fast simulation:

- High resolution models
- History-matching
- Optimization
- Uncertainty quantification
- More complex physics

How to improve performance?

- Decrease complexity
 - Physics
 - Upscale
 - Multiscale
- Increase computational power
 - Multicore systems with shared memory
 - Clusters with distributed memory
 - Manycore architectures (GPU, Xeon Phi)

Discretization in reservoir simulation



Forward simulation requirements

Robustness - Fully Implicit Method

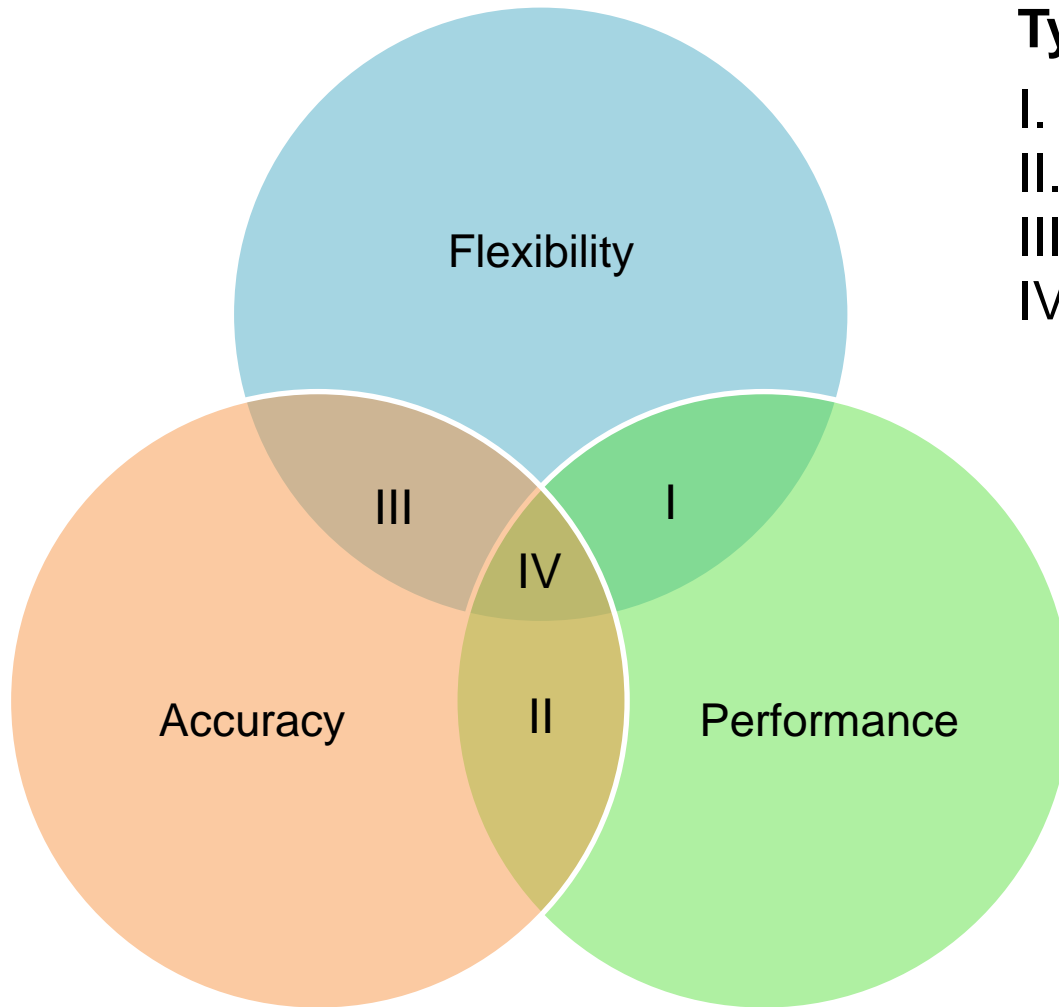
- is unconditionally stable
- results in highly nonlinear equations

Efficiency - nonlinear solution

- advanced nonlinear solvers
- physics-based linear solvers
- implementation on advanced architectures

The linearization procedure is important

Fully implicit: how to linearize equations?



Types of linearization:

- I. Numerical
- II. Analytical
- III. Automatic Differentiation
- IV. Operator-Based Linearization (OBL)

Operator form of equations

$$V\phi \left[\left(\sum x_{cj}\rho_j S_j \right)^{n+1} - \left(\sum x_{cj}\rho_j S_j \right)^n \right] - \Delta t \sum_{k \in L} \sum_{j=1}^{n_p} (x_{cj}\rho_j \lambda_j \Gamma)^l (p - p^l) = 0$$

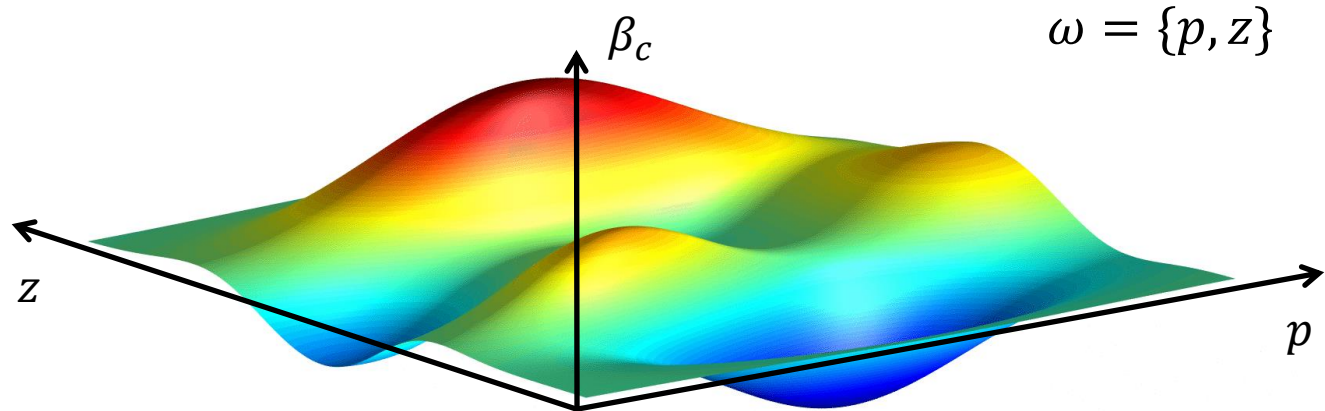


$$\phi_0 V [\alpha_c(\omega) - \alpha_c(\omega_n)] + \sum_k \Delta t \Gamma^l (\omega_1^l - \omega_1) \beta_c(\omega) = 0$$

$\omega = \{p, z_1, \dots, z_{n_c-1}\}$ (can include T or h for thermal)

$$\alpha_c(\omega) = c(p) \sum_{j=1}^{n_p} x_{cj}\rho_j S_j, \quad \beta_c(\omega) = \sum_{j=1}^{n_p} x_{cj}\rho_j^l \frac{k_{rj}^l}{\mu_j^l}$$

Operator-Based Linearization

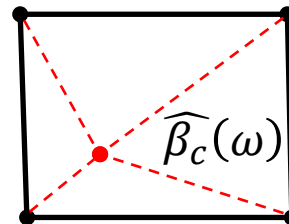


$$\beta_c(\omega^1) = \sum_{j=1}^{n_p} x_{cj}^l \rho_j^l \frac{k_{rj}^l}{\mu_j^l}$$

$$\beta_c(\omega^2) = \sum_{j=1}^{n_p} x_{cj}^l \rho_j^l \frac{k_{rj}^l}{\mu_j^l}$$

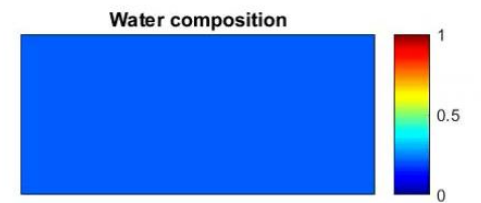
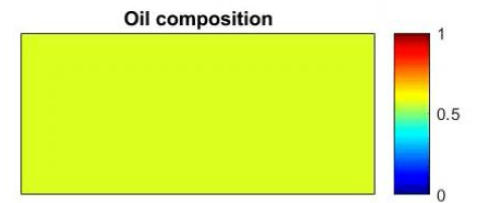
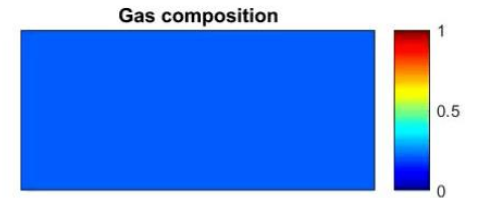
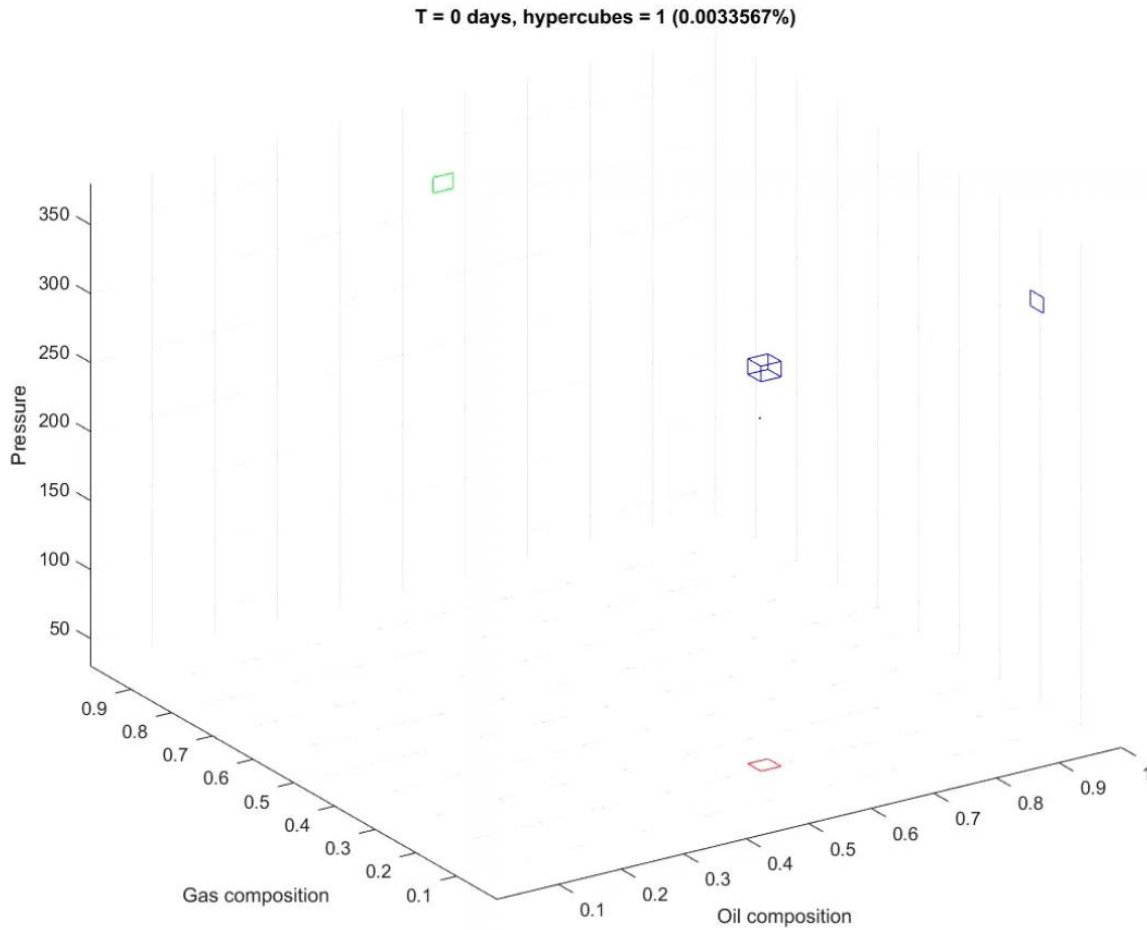
$$\beta_c(\omega^3) = \sum_{j=1}^{n_p} x_{cj}^l \rho_j^l \frac{k_{rj}^l}{\mu_j^l}$$

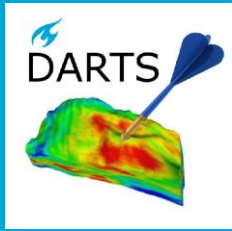
$$\beta_c(\omega^4) = \sum_{j=1}^{n_p} x_{cj}^l \rho_j^l \frac{k_{rj}^l}{\mu_j^l}$$



$$|\widehat{\beta}_c - \beta_c| \leq cV^2 \sup_{\omega} |\nabla^2 \beta_c|$$

Adaptive parametrization





Delft Advanced Research Terra Simulator in numbers

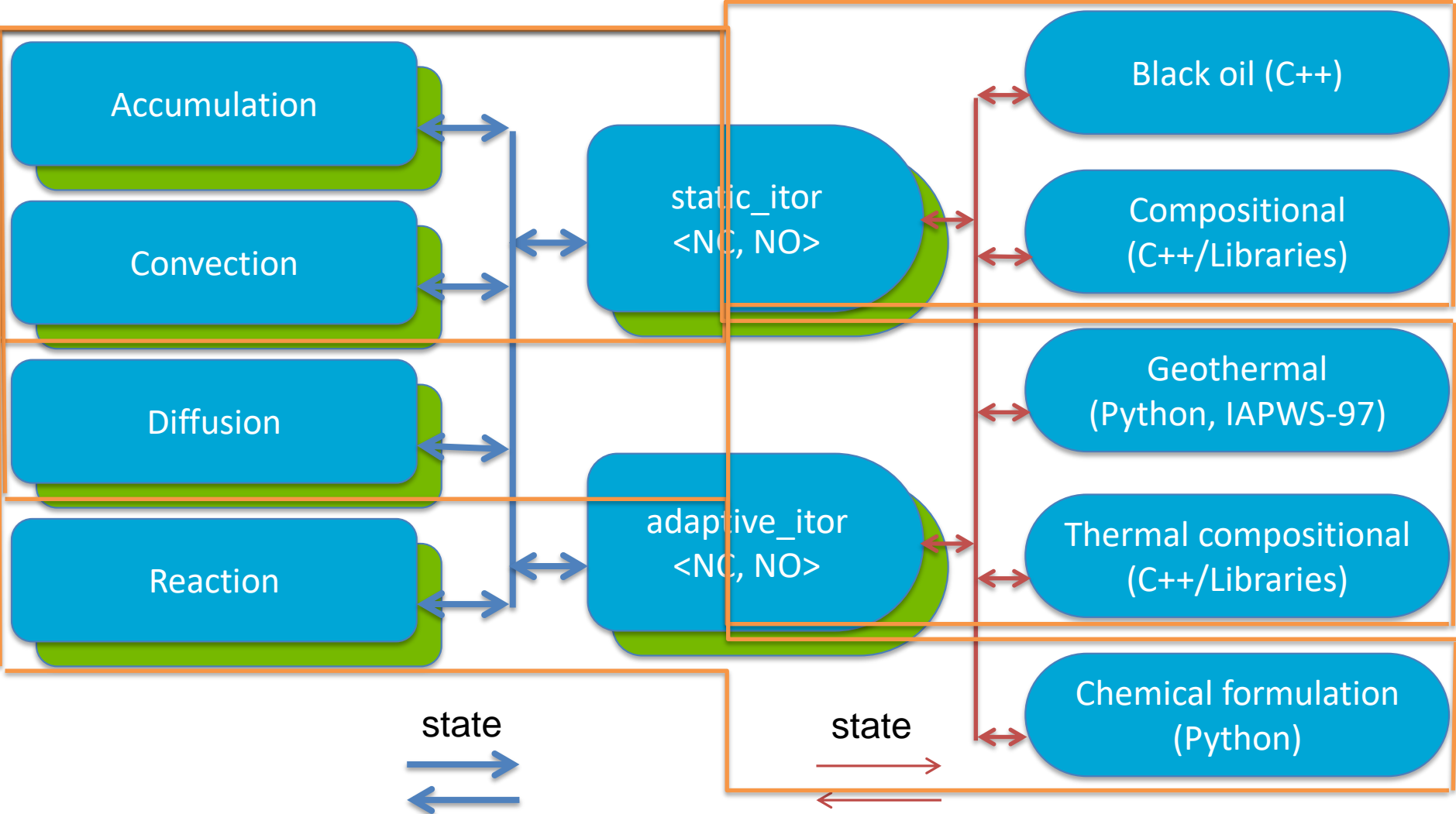
- 6 PhD and 1 PD projects
- 9 MSc projects defended so far
- Advance performance of simulation:
 - Around 100 times faster than average COMSOL model,
 - 3-5 times faster vs. state-of-the-art research simulators (ADGPRS, TOUGH2),
 - Close to performance of commercial simulators,
 - Fully GPU version is ready (6-15 times faster).
- Various physics included: convection, thermal conduction, diffusion, gravity, capillarity, chemistry (kinetic and equilibrium)
- Variety of applications: geothermal, black-oil, thermal-compositional, EOR, gas storage, hydrates etc.

<https://darts.citg.tudelft.nl/>

DARTS architecture

DARTS-engine: C++ & CUDA

DARTS-physics: hybrid



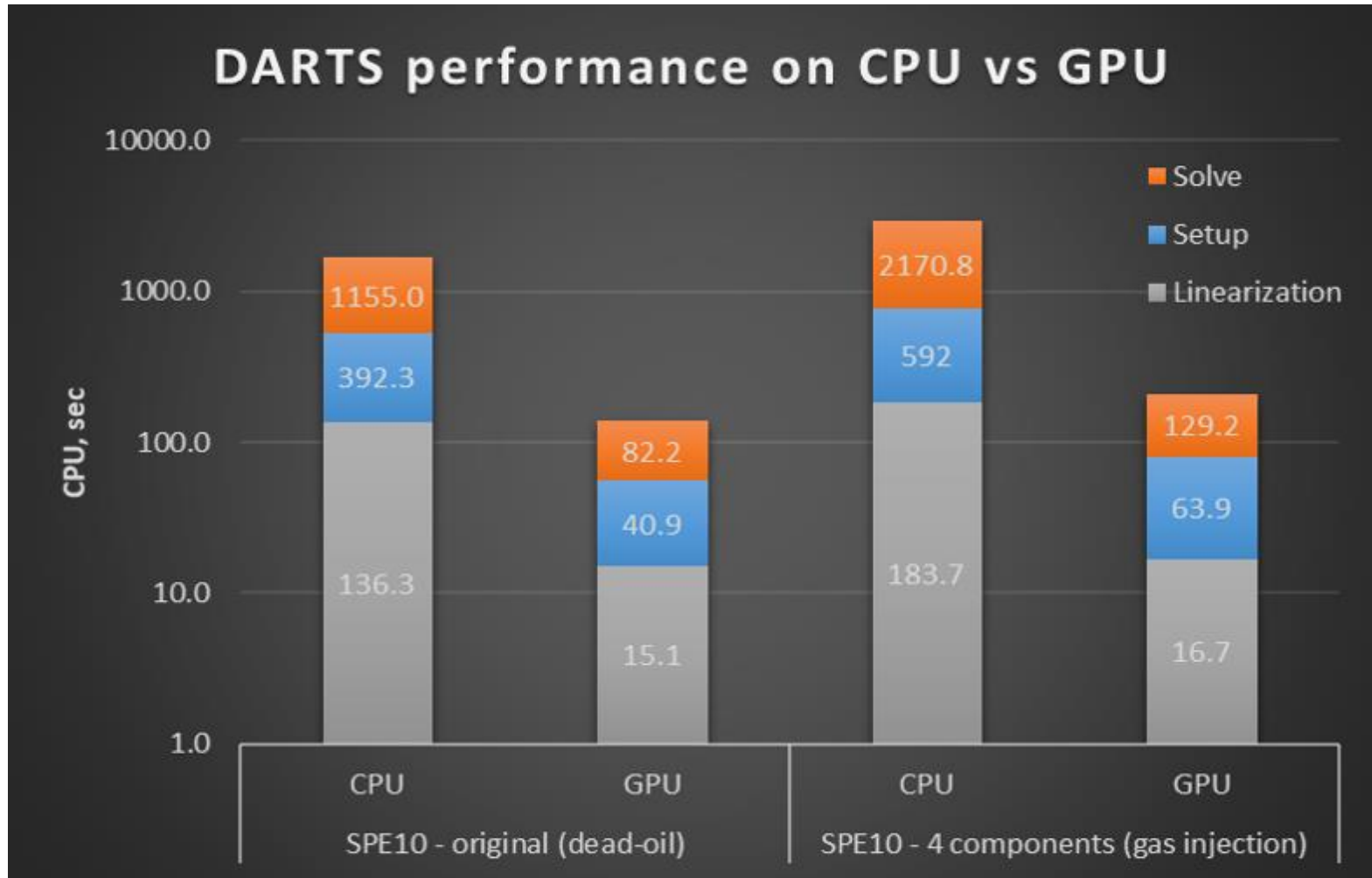
state
→
←

state
→
←

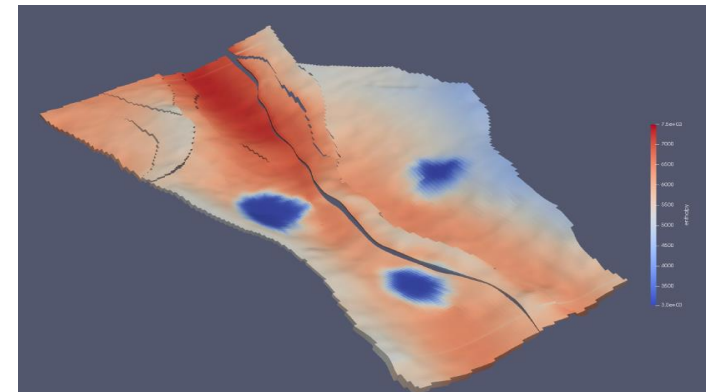
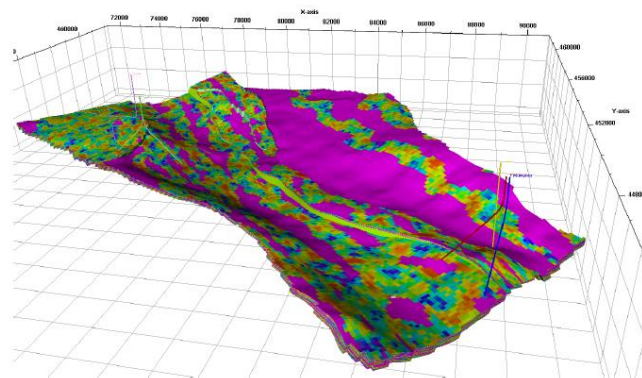
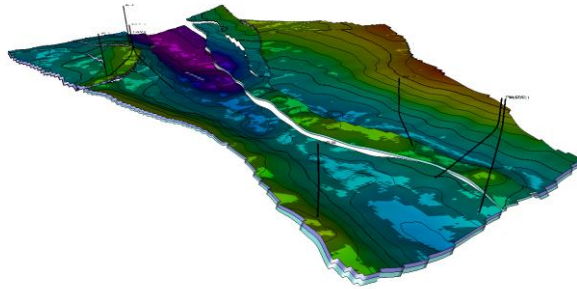
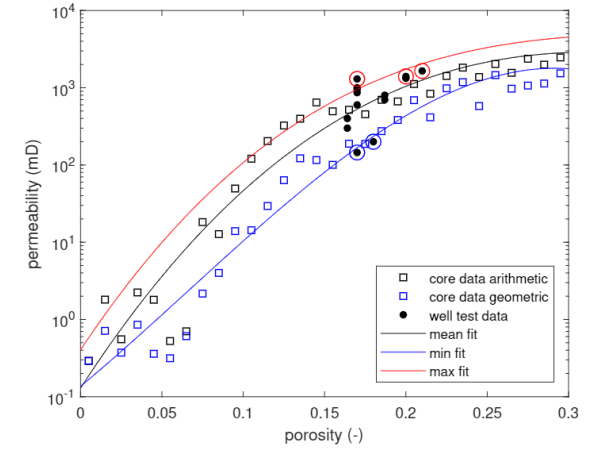
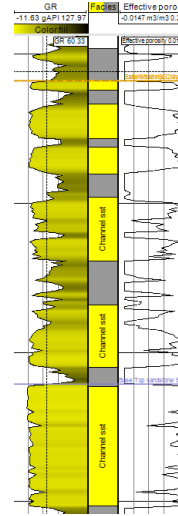
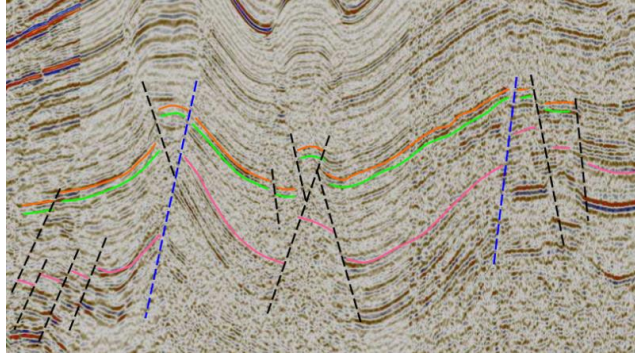
operator values & derivatives

operator values

DARTS-GPU



Den Haag project: sensitivity study

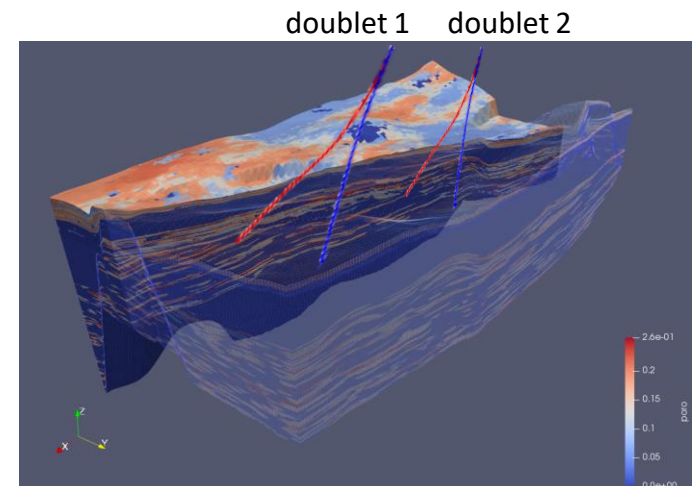
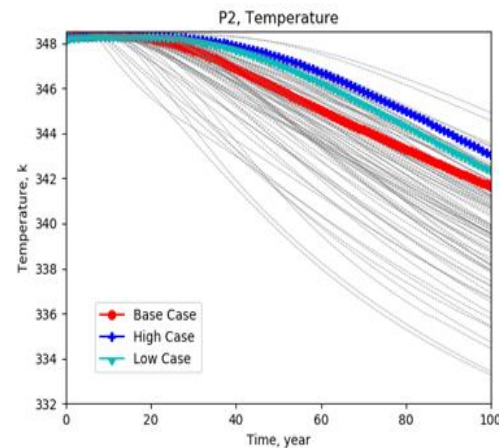
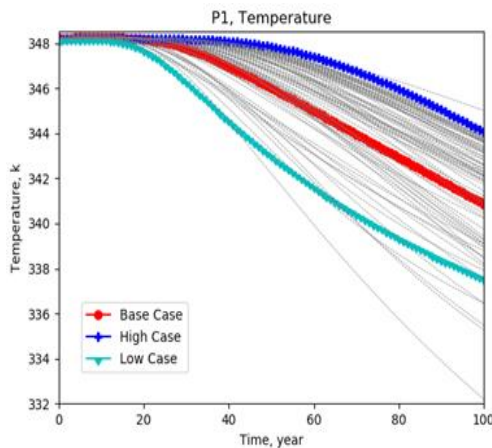
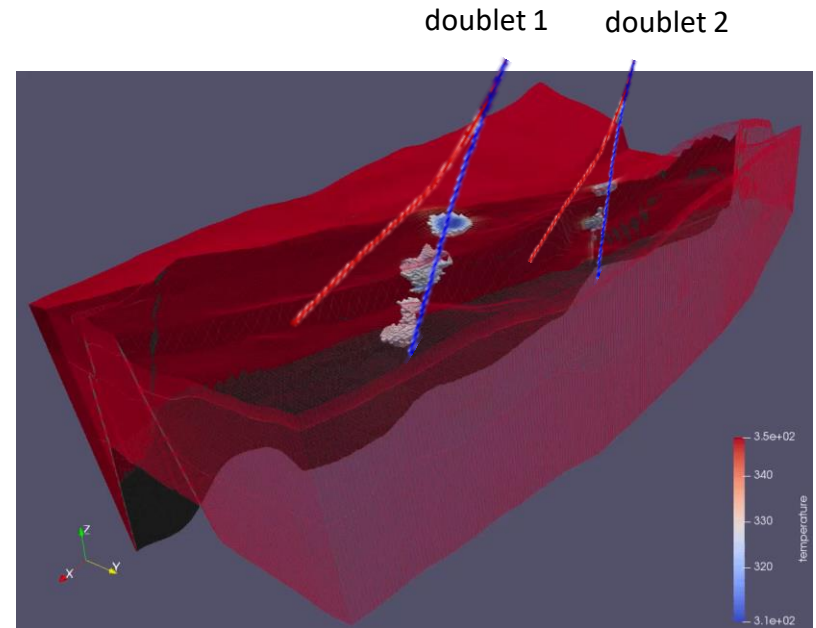


Perkins (2019)

CRECCIT project: sensitivity

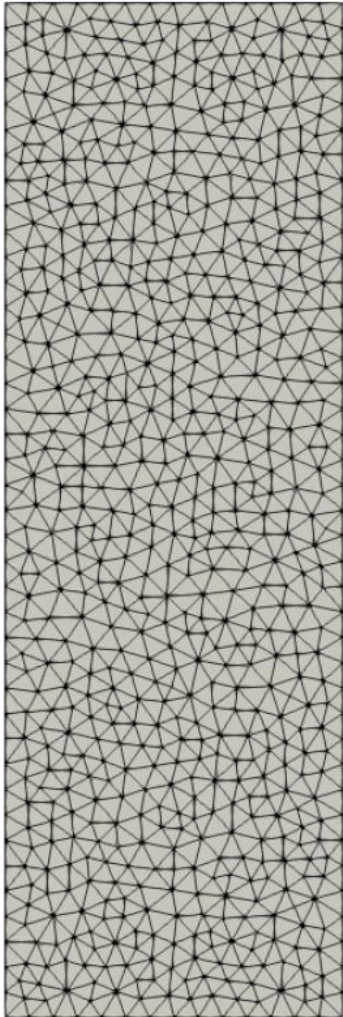
- One doublet has been drilled
- High uncertainty: well logs from the production well are only available
- Second doublet has been planned based on P50 case of first doublet
- We showed that use P50 scenario based only on one well data is misleading

3.2M grid blocks, 100 years of simulation



Adaptive Mesh Refinement

Level 0



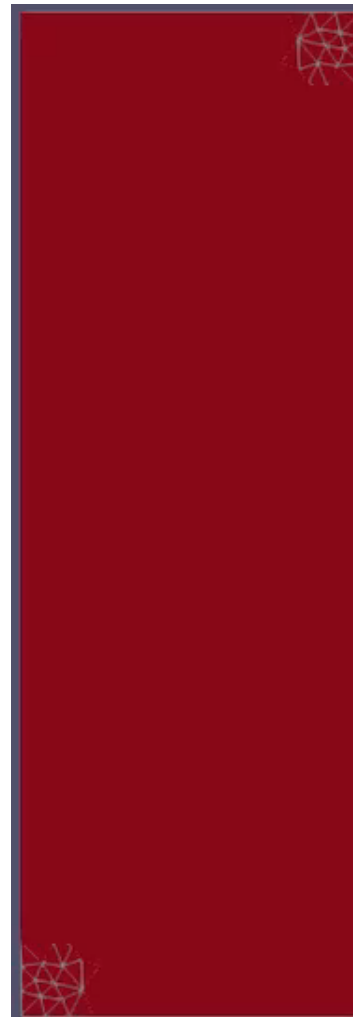
Level 1



fine



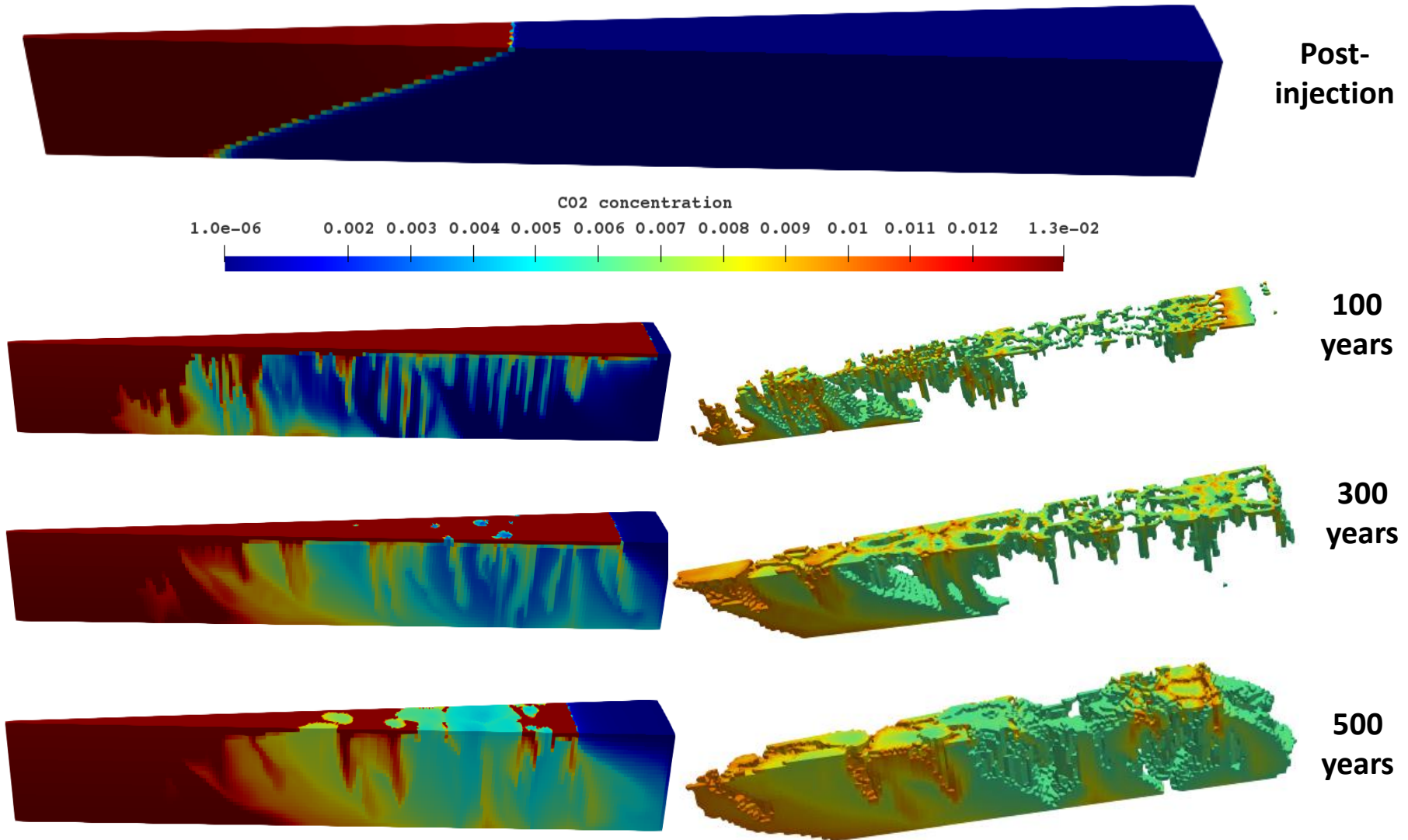
AMR



coarse



Supercritical CO₂ dissolution in aqueous brine



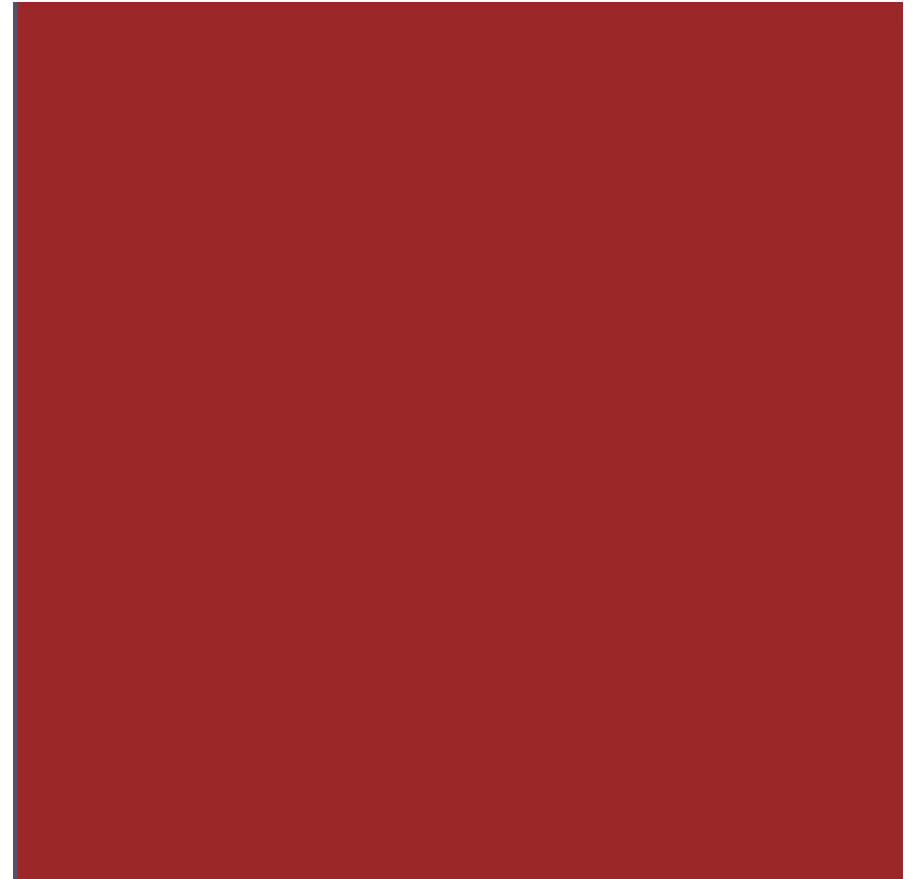
Carbonate dissolution

Fast kinetic



$$k_{rate} = 0.005 \text{ [1/day]} \rightarrow Da = 12.5$$

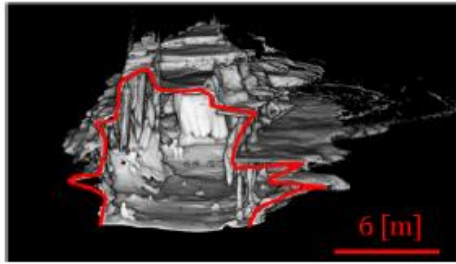
Slow kinetic



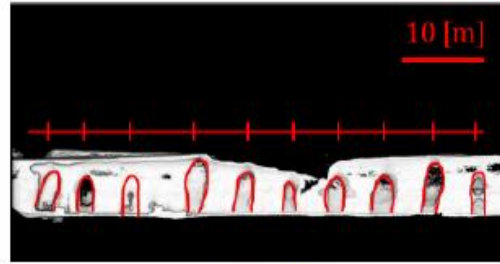
$$k_{rate} = 5e-7 \text{ [1/day]} \rightarrow Da = 1.25e-3$$

de Hoop and Voskov (2018)

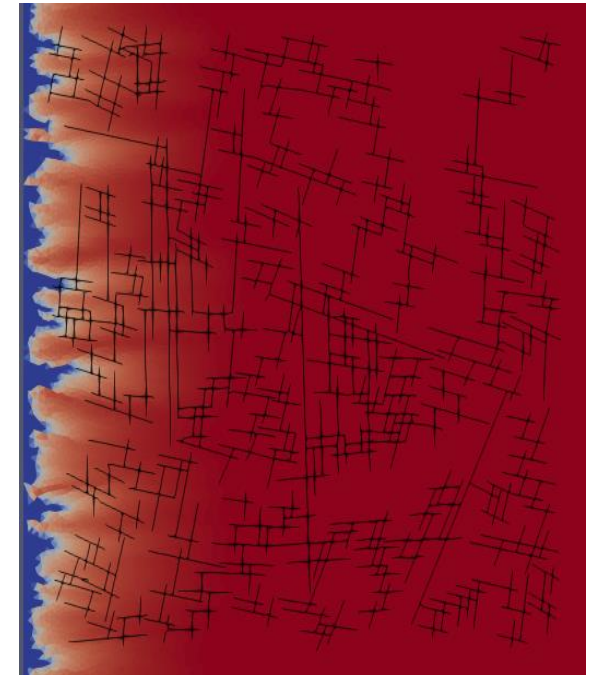
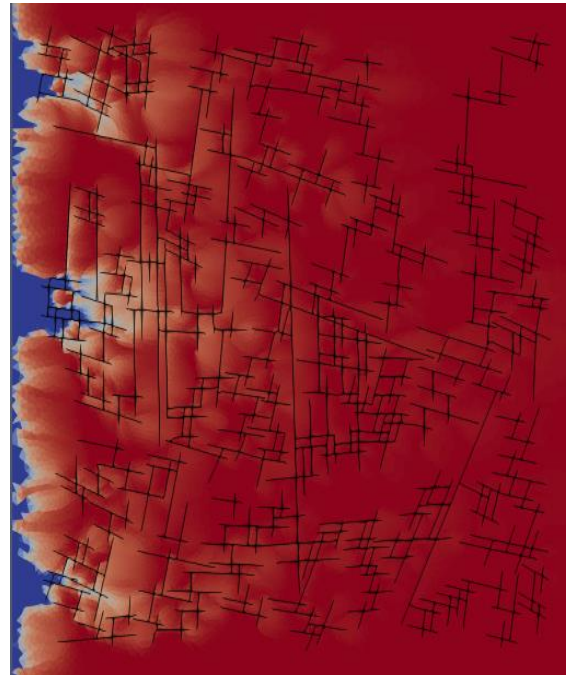
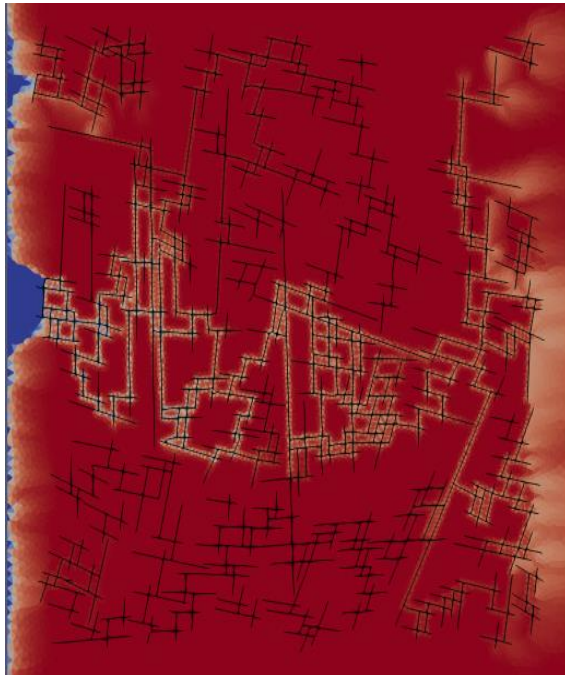
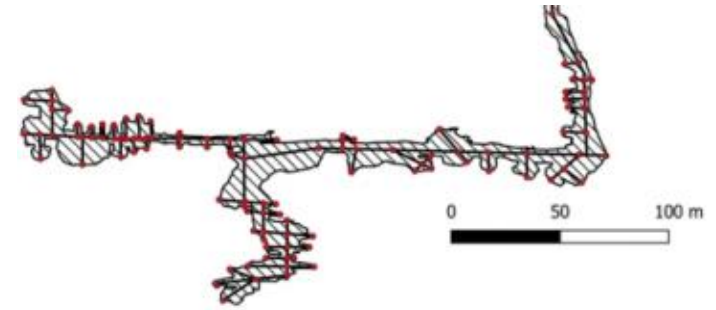
Modeling of dissolution in fractured networks



Cave "Ioio"



Cave "Torrinha"

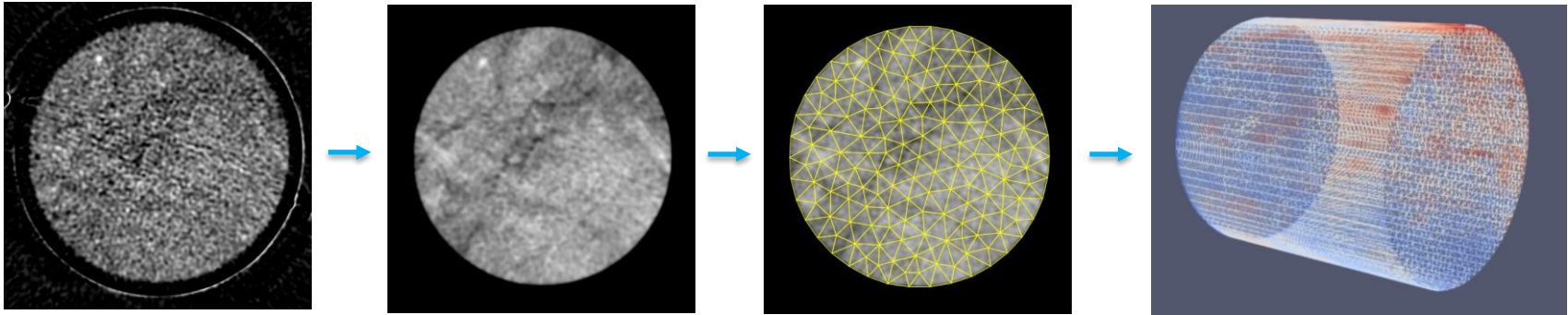


Decrease fracture aperture

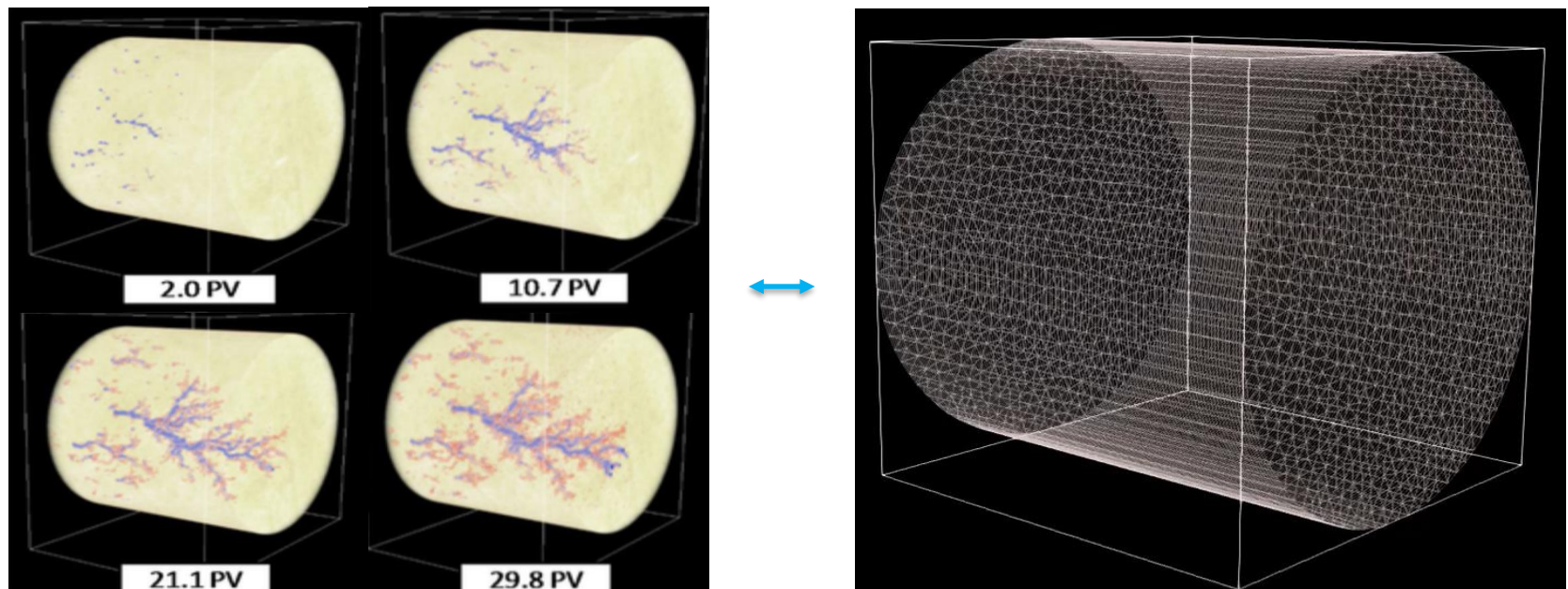


Modeling of dissolution in core

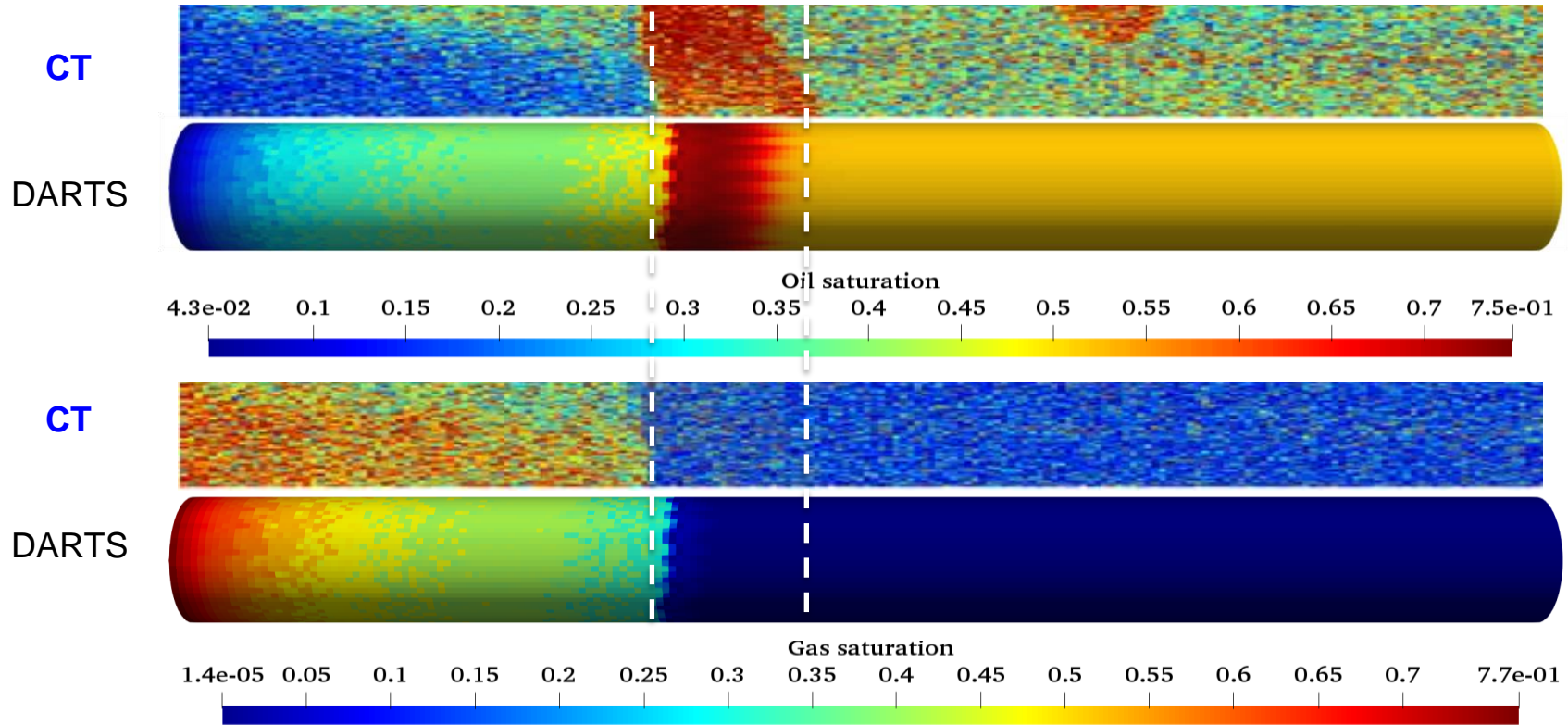
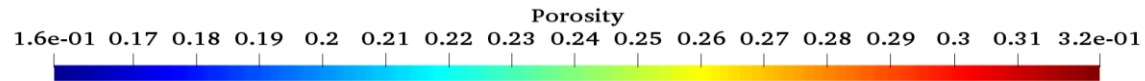
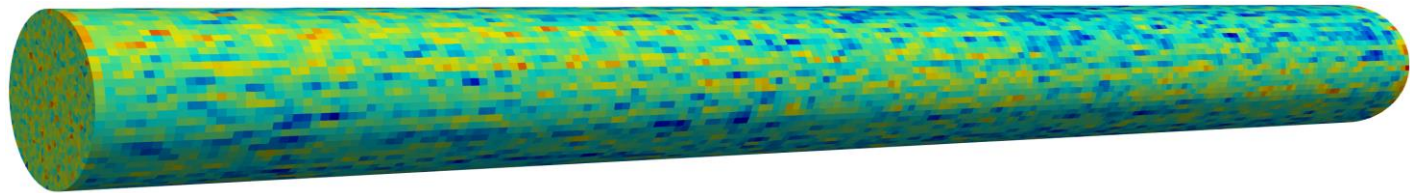
Step 1: porosity interpretation (image subtraction, filtering, gridding)



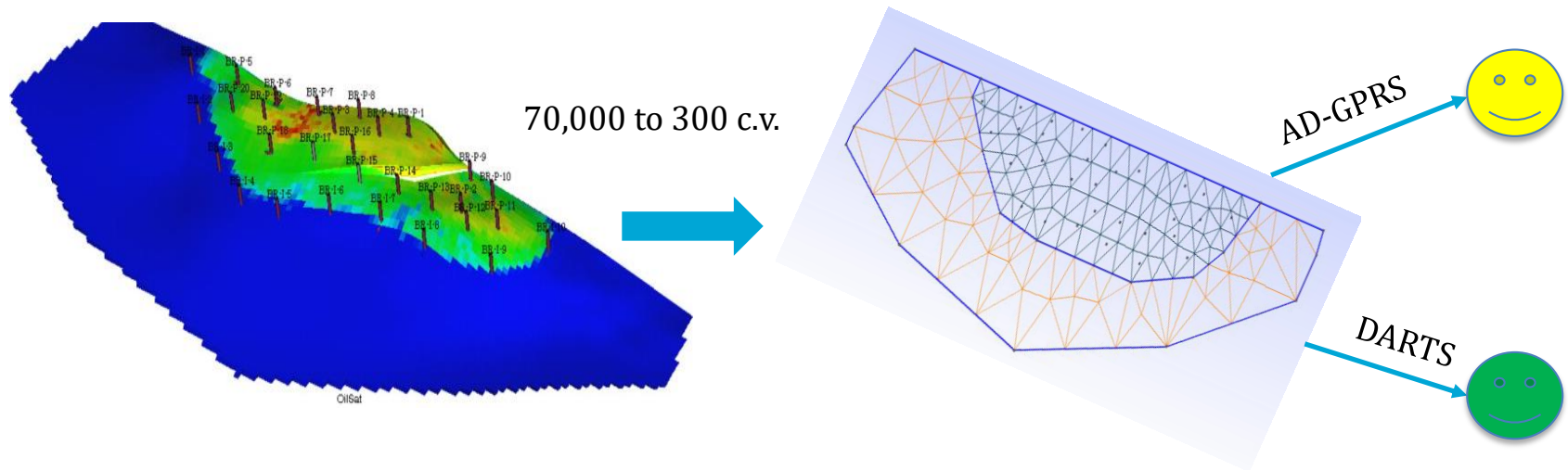
Step 2: modeling of dissolution (combination of DARTS + PHREEQC)



Modeling of foam CT experiments



Physics-based data-driven proxy model



	High fidelity model	Proxy Model
Control volumes	~70 thousand	~300
Reservoir properties	Realization #73	Regressed to the data
Production data	20*120 days	20*120 days + coarsening
Simulation time (AD-GPRS)	645 seconds	8.3 seconds
Simulation time (DARTS)	97 seconds	0.46 -> 0.03 seconds

Conclusion

- OBL framework proves to be
 - Accurate for various applications,
 - Flexible for complex extensions,
 - Highly efficient in terms of CPU,
 - Extendable to advanced architectures.
- New generation research code DARTS
 - New release will be delivered soon,
 - Easy to work with, but knowledge of reservoir simulation and Python is required.

References

- Voskov, D., 2017: Operator-based linearization approach for modeling of multiphase multicomponent flow in porous media. Journal of Computational Physics.
- Khait, M. and Voskov, D., 2018: Adaptive Parameterization for Solving of Thermal/Compositional Nonlinear Flow and Transport With Buoyancy. SPE Journal.
- DARTS, 2019: Delft Advanced Research Terra Simulator. <https://darts.citg.tudelft.nl/>
- Wang Y., Voskov D., Khait M., Bruhn D., 2020. An efficient numerical simulator for geothermal simulation: A benchmark study, Applied Energy, 264, 114693, ISSN 0306-2619. <https://doi.org/10.1016/j.apenergy.2020.114693>.
- Perkins, D., 2019: Reservoir Simulation for Play-based Development of Low Enthalpy Geothermal Resources: Application to the Delft Sandstone, Den Haag, MSc Thesis, TU Delft. <http://resolver.tudelft.nl/uuid:3b0a34c9-2080-4361-b36d-7b2d7095962f>
- Saeid, S., Wang, Y., Daniilidis, A., Khait, M., Voskov, D. and Bruhn, D., 2020: Lifetime and Energy Prediction of Geothermal Systems: Uncertainty Analysis in Highly Heterogeneous Geothermal Reservoirs (Netherlands), World Geothermal Congress. <https://pangea.stanford.edu/ERE/db/WGC/papers/WGC/2020/22157.pdf>
- Jones, E., 2019: Applications of unstructured multi-level grid to thermal-reactive flow and transport in porous media, MSc Thesis, TU Delft. <http://resolver.tudelft.nl/uuid:3b0a34c9-2080-4361-b36d-7b2d7095962f>
- de Hoop, S., Voskov, D. and Bertotti, G., 2019: Uncertainty quantification and history matching for naturally fractured carbonate reservoirs. Third EAGE WIPIC Workshop: Reservoir Management in Carbonates, Qatar. <https://www.earthdoc.org/content/papers/10.3997/2214-4609.201903106>
- Morshuis, N., 2019. An improved carbon dioxide thermodynamic model applied for reservoir simulation. MSc thesis, Delft University of Technology. <http://resolver.tudelft.nl/uuid:41291fae-70ec-43ae-8973-1d7003a76f8e>
- de Hoop, S., Voskov, D., 2019: Parametrization Technique for Reactive Multiphase Flow and Transport, In. SIAM Geosciences. https://www.pathlms.com/siam/courses/11267/sections/14643/video_presentations/128804
- Snippe, J., Berg S., Ganga, K., Brussee, N., and Gdanski, R., 2019: Experimental and numerical investigation of wormholing during CO2 storage and water alternating gas injection. Int. Journal of Greenhouse Gas Control. <https://doi.org/10.1016/j.ijggc.2019.102901>
- Margert, A., 2019: Dissolution Patterns Prediction in Carbonate System, MSc Thesis, TU Delft
- Tang, J., Vincent-Bonnieu, S., & Rossen, W. R., 2019. CT coreflood study of foam flow for enhanced oil recovery: The effect of oil type and saturation. Energy, 188, 116022. <https://doi.org/10.1016/j.energy.2019.116022>
- Blinovs, A., 2019. Physics-Based Data-Driven Model for Short-Term Production Forecast, MSc thesis, Delft University of Technology.