Simulator-based Bayesian inference of enhanced geothermal reservoir properties

HELSINGIN YLIOPISTO
HELSINGFORS UNIVERSITET
UNIVERSITY OF HELSINKI
MATEMAATTIS-LUONNONTIETEELLINEN TIEDEKUNTA
MATEMATISK-NATURVETENSKAPLIGA FAKULTETEN
FACULTY OF SCIENCE

Karlsruhe Institute of Technology

Kwabena Atobra[1], Gregor Hillers[1,2], Vladimir Lyakhovsky[3], Eyal Shalev[3], Arto Klami[4], and Ulpu Remes[5]

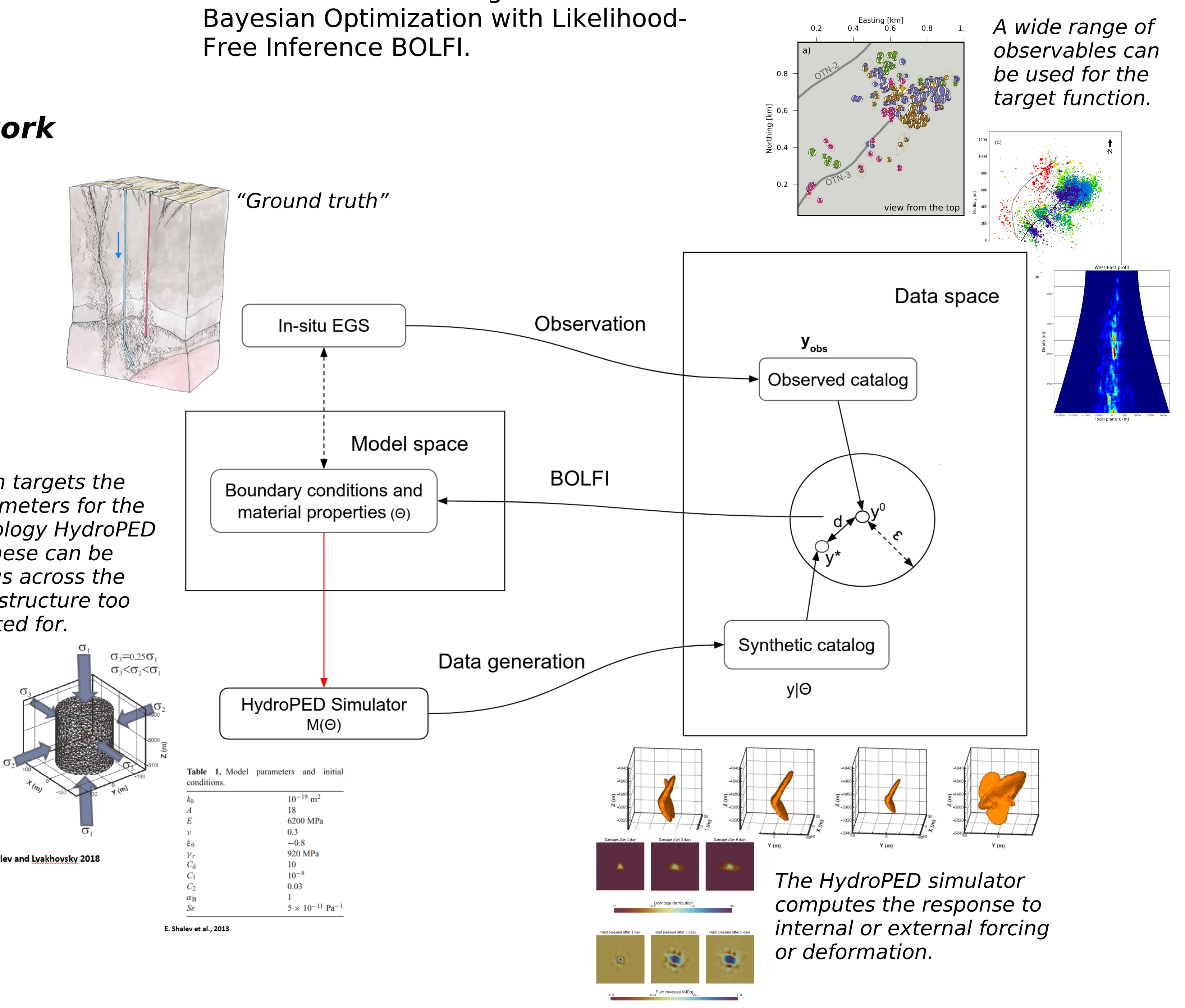
[1]Institute of Seismology, University of Helsinki, Helsinki, Finland
[2]Geothermal Energy & Reservoir Technology, Institute of Applied Geosciences, KIT, Karlsruhe, Germany
[3]Geological Survey of Israel, Jerusalem, Israel
[4]Department of Computer Science, University of Helsinki, Helsinki, Finland
[5]Department of Mathematics and Statistics, University of Helsinki, Helsinki, Finland

mail: gregor.hillers@helsinki.fi
web: bit.ly/HILatHEL

APPROACH

We constrain reservoir properties using a damage rheology forward solver in combination with an algorithm for Bayesian Optimization with Likelihood-Free Inference BOLFI.

Framework

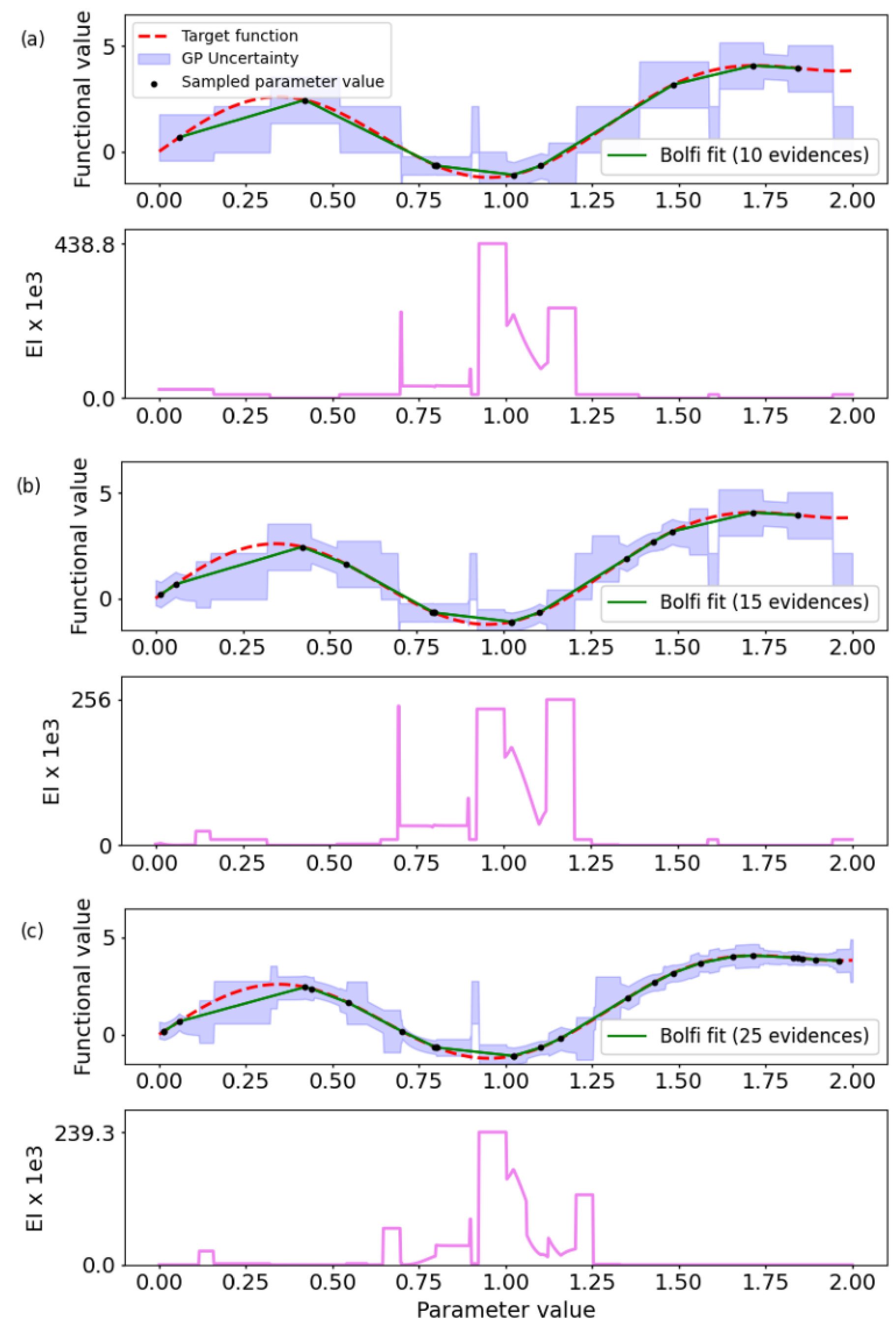


A wide range of observables can be used for the target function.

The inversion targets the optimal parameters for the damage rheology HydroPED simulator. These can be homogeneous across the domain, but structure too can be inverted for.

The HydroPED simulator computes the response to internal or external forcing or deformation.

Conceptual one-parameter illustration of BOLFI



BOLFI in a nutshell

The likelihood refers to an analytical expression describing the probability of observing an output given specific values of the model parameters. Here, the direct likelihood evaluation is not tractable => likelihood-free inference.

BOLFI uses simulations to learn a statistical model to approximate the likelihood.

In the figure, the underlying target function (red line) describes the discrepancy between the simulated and observed data for different parameter values. The aim is to learn this target function using outputs from iterative forward simulations. This learning is achieved by constructing the green indicated Gaussian Process GP surrogate model obtained from the simulated outputs guided by the acquisition function which determines the next sample.

The panels indicate updated surrogate models obtained from intelligent acquisition sampling of new points. The lower panels in each case represent the acquisition function that tells the algorithm which parameter should be sampled in the next iteration.

ESTIMATING AMBIENT RESERVOIR STRESSES

In this pilot we invert for the ambient reservoir stress. We simulate the observed data in response to a Helsinki-EGS-informed injection with the HydroPED tool that is also used in the inversion. We analyze the inversion results using 200 or 500 forward simulations, and using the spatial variation of the event count or the potency release for the inversion.

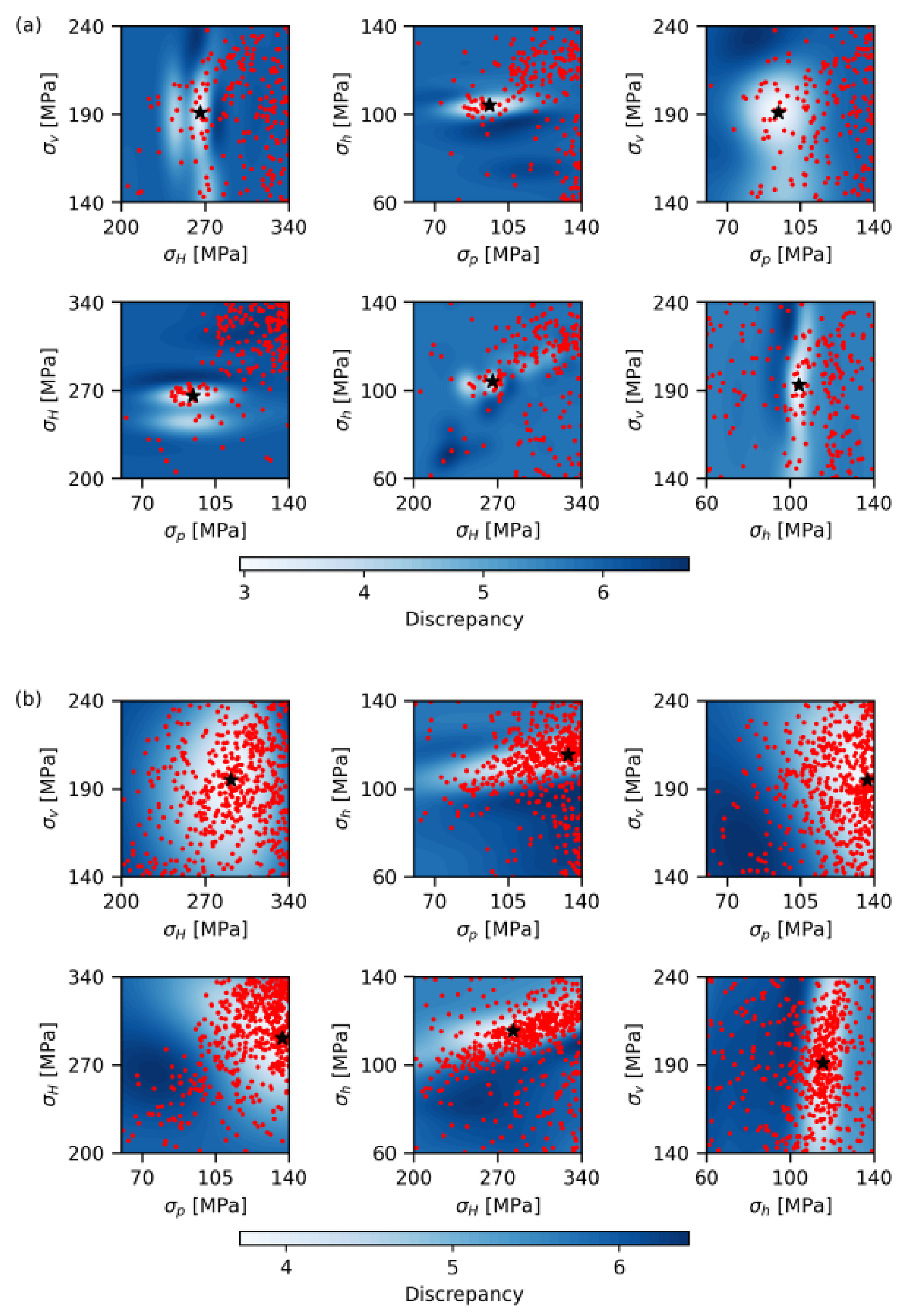
Results from event count summaries

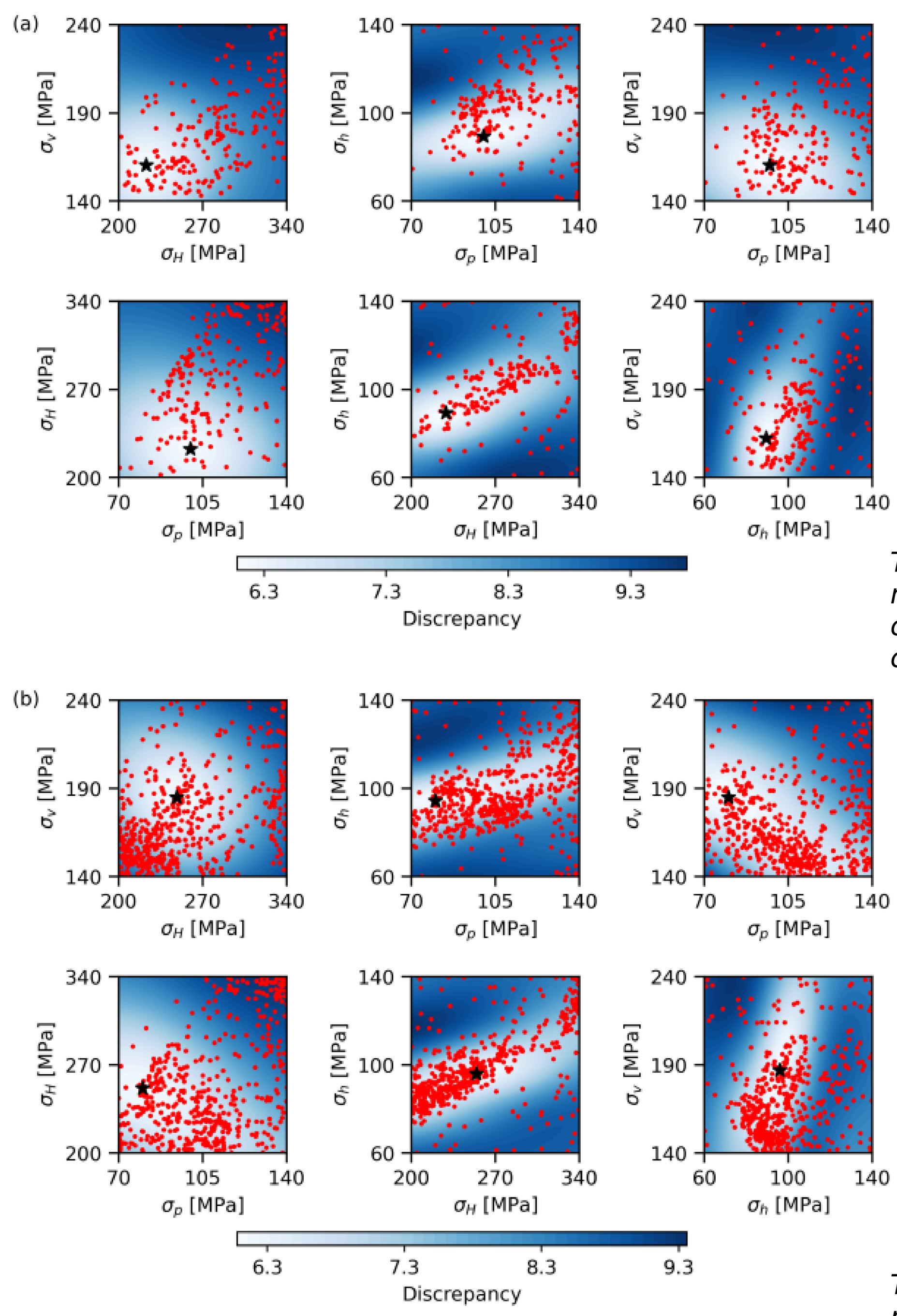
Results from potency summaries

Inversion contour plots

***200** iterations*

***500** iterations*



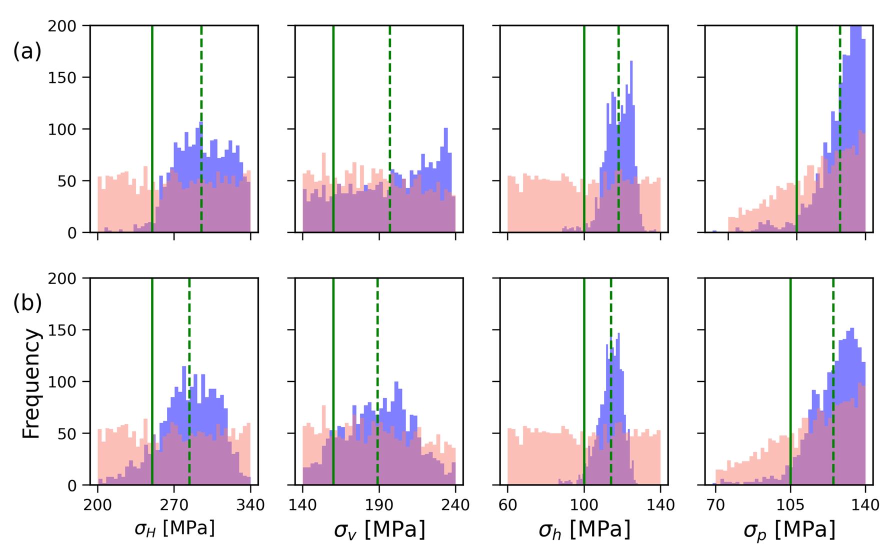


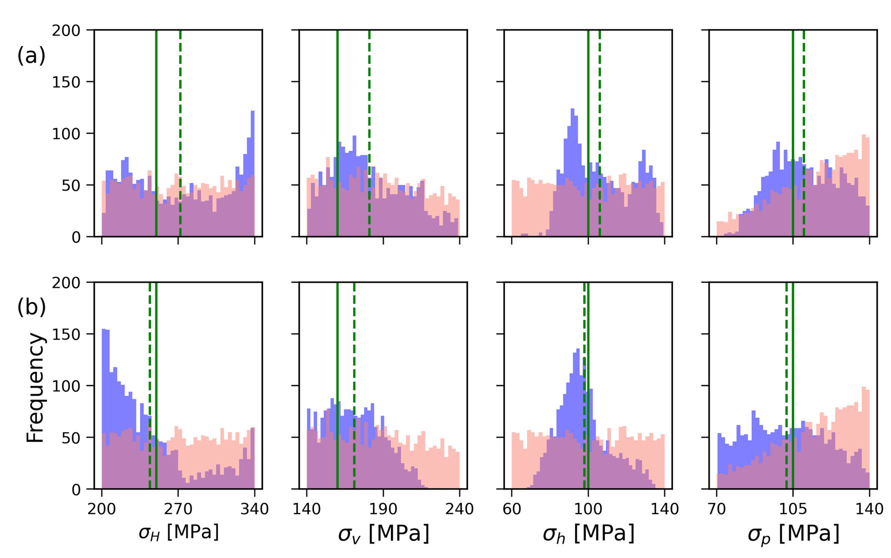
The discrepancy represents the learned model for different parameter value combinations (green line in the 1D model concept).

Sampled posterior distributions

***200** iterations*

***500** iterations*





The posterior distribution describes the probability that a system is governed by the model parameter given the observed data.

CONCLUSIONS

Our pilot application of the HydroPED – BOLFI inversion tool suggests its effectiveness in constraining posterior distributions of key reservoir parameters.

For our pilot stress inversion we find that the spatially variable potency release provides better estimates of the ambient stress state.

The implementation can be extended to a wide range of target observations, and to investigate the trade-off in governing HydroPED parameters for a better understanding of the nonlinearity and complexity of the stimulation problem.

References

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