Ensemble Methods for Geothermal Model Calibration

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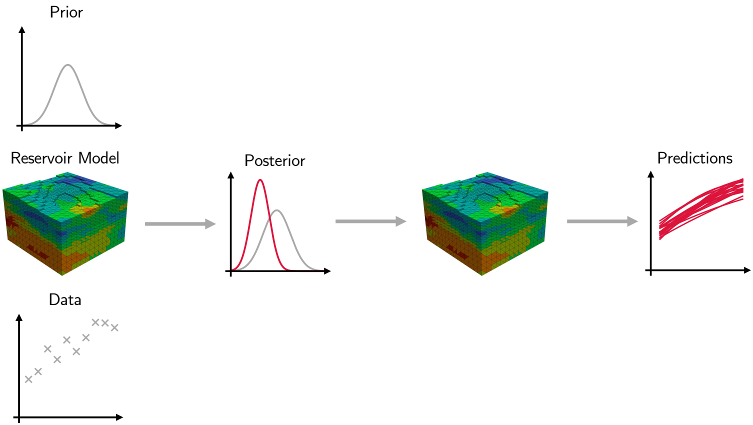
Reservoir Model Calibration in the Bayesian Framework



Ensemble Methods: an Overview

Ensemble methods iteratively update a group of sets of model parameters (the ensemble) to produce an approximation to the posterior.

Ensemble methods are:

- **Derivative free:** gradients are estimated using the ensemble members
- **Efficient:** they can produce accurate results using $\mathcal{O}(1000)$ simulations
- **Embarrassingly parallel:** the entire ensemble can be simulated simultaneously at each iteration

Key developments include:

- **Ensemble Randomised Maximum Likelihood** (Chen and Oliver 2013)
- **Multiple Data Assimilation** (Emerick and Reynolds 2013)
- **Ensemble Kalman Inversion** (Iglesias *et al*. 2013, Iglesias and Yang 2021)

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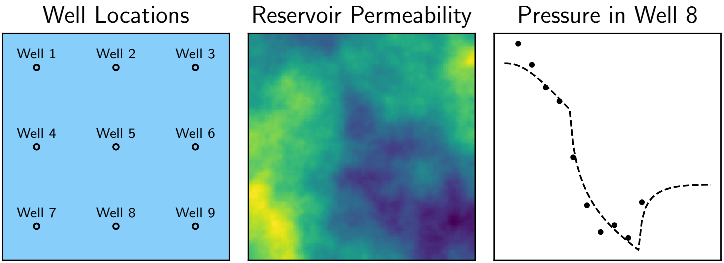
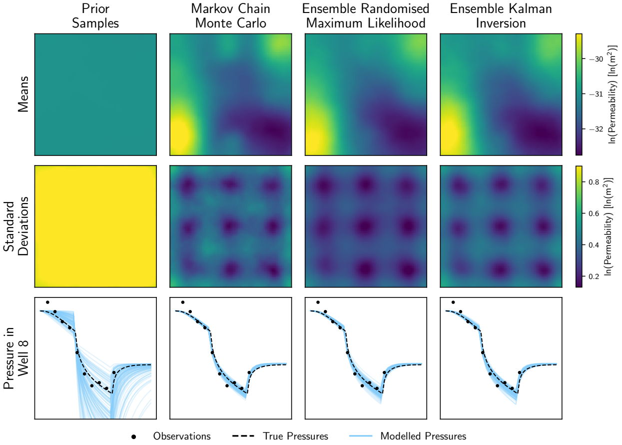
Ensemble Methods: an Illustrative Example

To compare ensemble methods to exact sampling methods, we consider the problem of estimating the permeability of an oil reservoir.

- The reservoir operates over a production period of 120 days
- 10 noisy pressure measurements are collected at each well



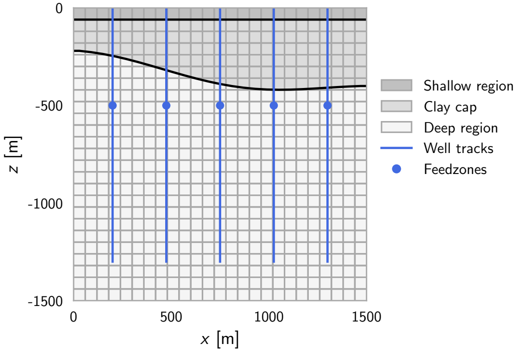
Ensemble Methods: an Illustrative Example



Model Geometry

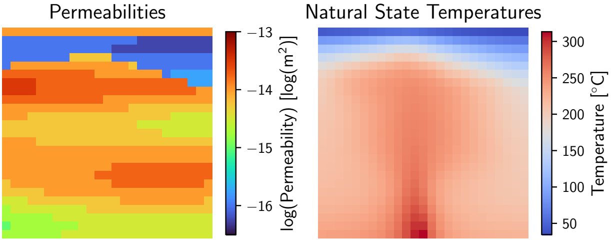
We consider a synthetic, 2D slice model, which contains:

- Two high-permeability regions separated by a low-permeability clay cap
- Five production wells operating at prescribed rates
- A hot mass upflow at the centre of the base



True Permeabilities and Natural State Temperatures

The true system is generated using a sample from the prior.



We aim to infer:

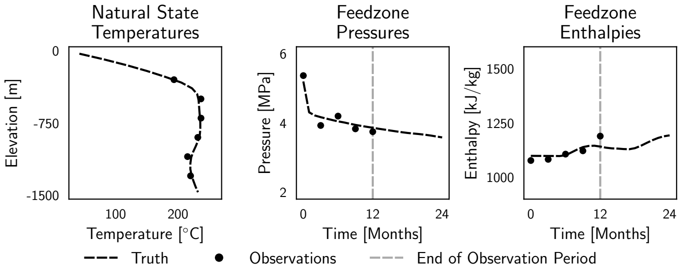
- The location of the bottom surface of the clay cap
- The (isotropic) permeability in each cell of the model
- The magnitude of the mass upflow at the base of the model

Observations

We consider a combined natural state and production history simulation.

The noisy observations consist of:

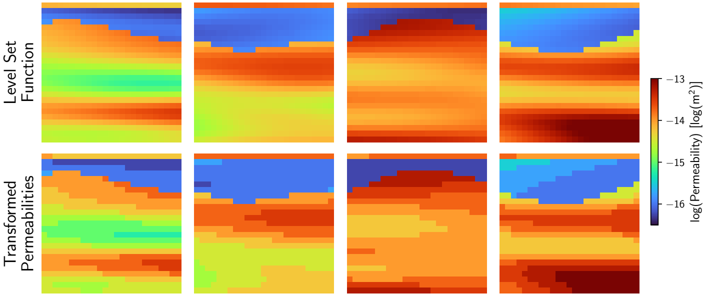
- 30 natural state temperature measurements
- 25 feedzone pressure measurements
- 25 feedzone enthalpy measurements



Prior Parametrisation

To characterise the prior, we use:

- A Gaussian process for the bottom surface of the clay cap
- The level set method for the permeability in each region
- A uniform distribution for the magnitude of the mass upflow



Experimental Setup

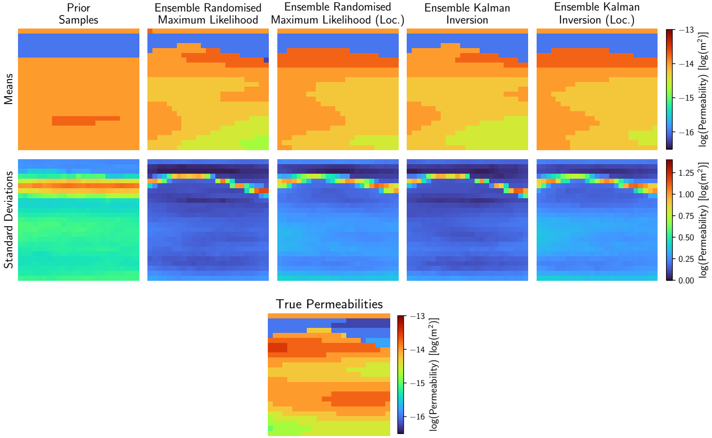
We investigate:

- The differences between Ensemble Randomised Maximum Likelihood and Ensemble Kalman Inversion
- The effect of localisation on the results of each method

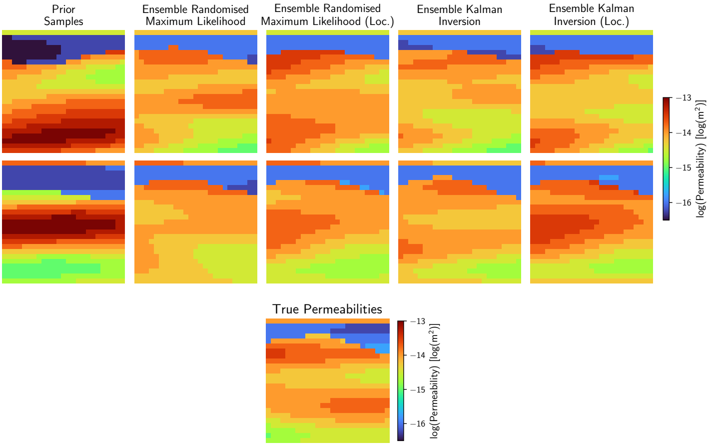
All experiments are performed using Waiwera.

- We use 100 ensemble members for each experiment
- In all experiments, between 1000 and 3000 simulations are required
- In all experiments, the model failure rate is $\approx 10\%$

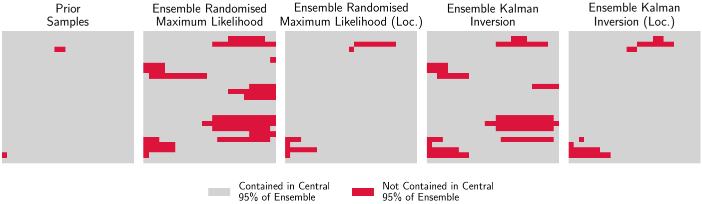
Posteriors


Prior Samples
Ensemble Randomised Maximum Likelihood
Ensemble Randomised Maximum Likelihood (Loc.)
Ensemble Kalman Inversion
Ensemble Kalman Inversion (Loc.)
Means
Standard Deviations
−13
−14
−15
−16
log(Permeability) [log(m^2)]
1.25
1.00
0.75
0.50
0.25
0.00
log(Permeability) [log(m^2)]
True Permeabilities
−13
−14
−15
−16
log(Permeability) [log(m^2)]

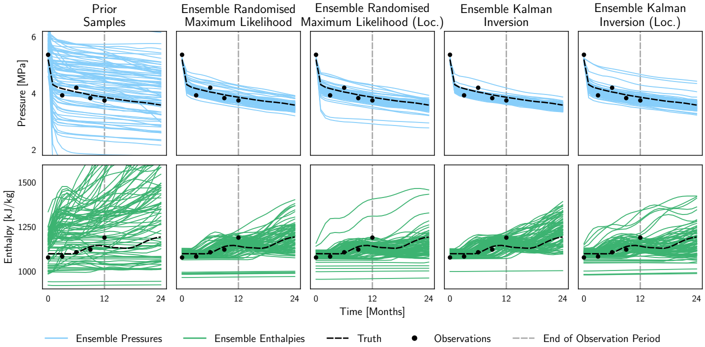
Ensemble Members



Approximate Credible Intervals



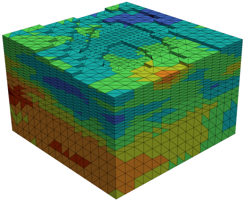
Predictions



Conclusions and Next Steps

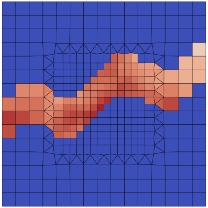
Some key conclusions:

- Ensemble methods show potential for efficient reservoir model calibration
- Localisation appears useful in maintaining ensemble spread



Next steps include:

- Experimenting with larger models
- Testing additional parameters and parametrisations
- Identifying methods for dealing with failed simulations



References

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