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Can history matching mess up my dual-porosity model?

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ORIGINAL PAPER

History matching of dual continuum reservoirs—preserving consistency with the fracture model

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Abstract Ensemble- and optimization-based parameter estimation is commonly used to calibrate simulation models of fractured reservoirs to measured data. Traditionally, statistical data on small-scale fractures are upscaled to a dual continuum model in a single step, and the subsequent history matching procedure makes adjustments to the upscaled parameters. In this paper, we show that the resulting reservoir models may be inconsistent with the initial fracture description, meaning that the reservoir parameters do not correspond to a physically valid combination of fracture parameters. A number of numerical examples is provided, which illustrate why and when the problem occurs. We uti-

1 Introduction

Fractures in geological formations are of importance in petroleum production, groundwater contamination assessment, geothermal energy production, and CO_2 storage. In all of these applications, assisted history matching through residual minimization or bayesian inversion is commonly applied [17]. A particular challenge with fractured reservoirs is that the reservoir parameters, such as permeability and porosity, originates from *upscaling* of a fracture network geometry. By perturbing the reservoir parameters individually to match production history, one runs the

Motivation: Staying on the manifold

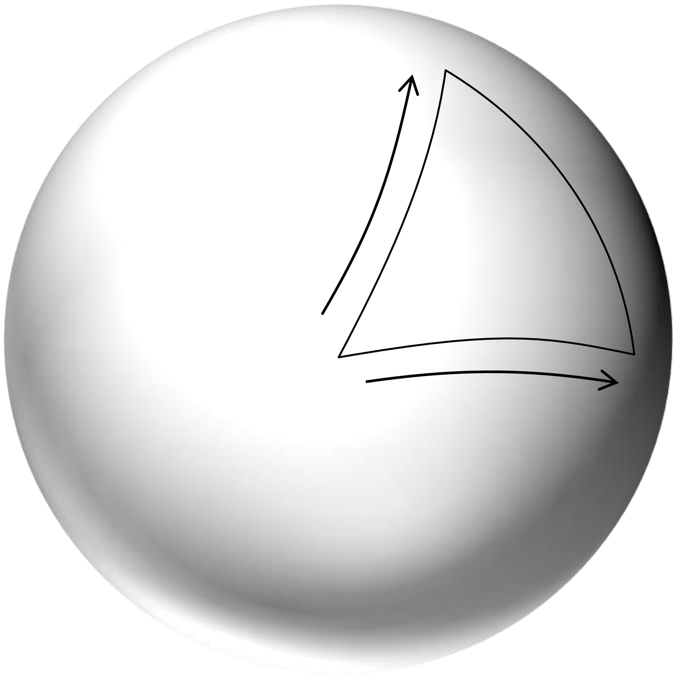
What happens if you apply history matching on upscaled fracture parameters?

$$\boldsymbol{r} = \begin{bmatrix} \text{Aperture} \\ \text{Fracture density} \\ \text{Upscaling error} \end{bmatrix}$$

$$\boldsymbol{r} = \begin{bmatrix} \text{Permeability} \\ \text{Porosity} \\ \text{Transfer coefficient} \end{bmatrix}$$

Motivation: Staying on the manifold

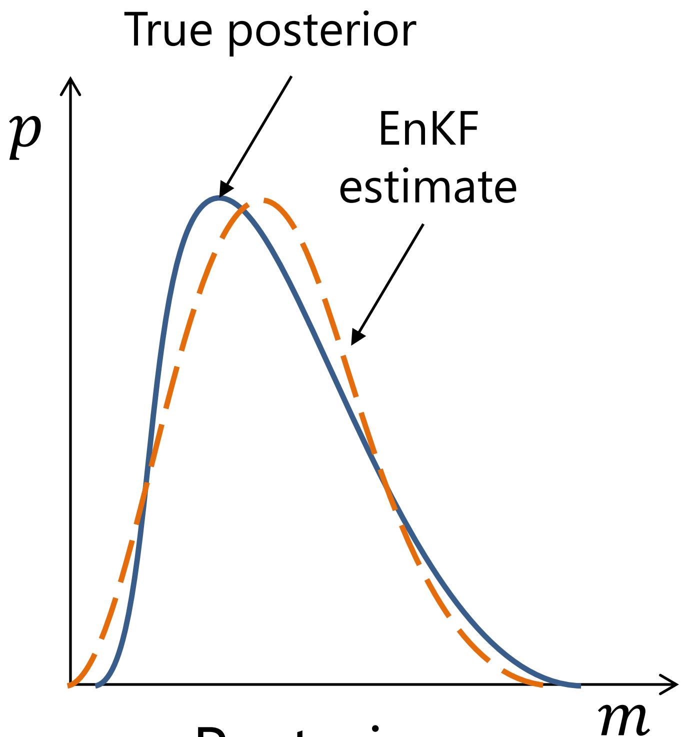
What happens if you apply history matching on upscaled fracture parameters?



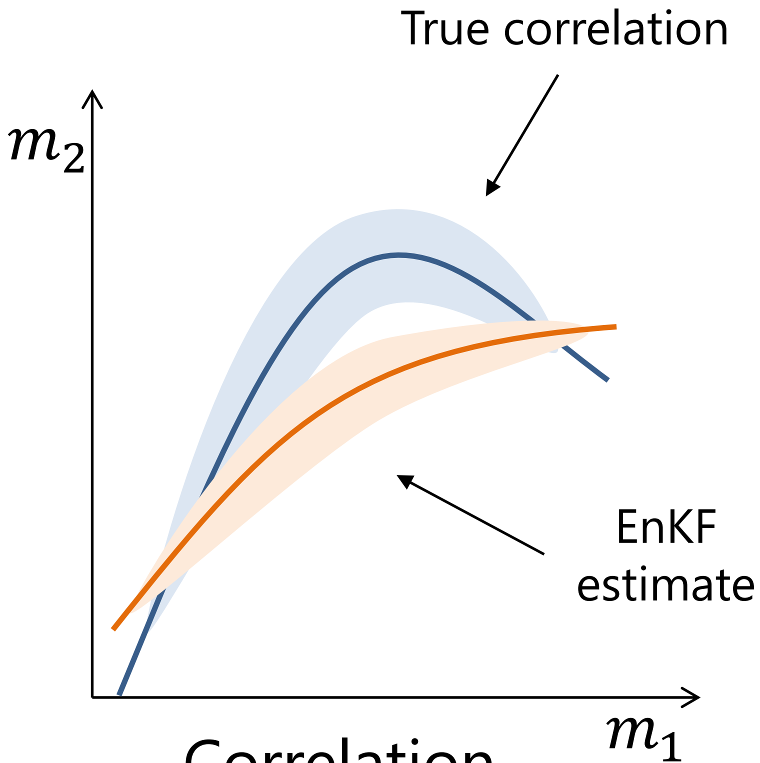
$$\boldsymbol{r} = \begin{bmatrix} R\sin\phi\cos\theta \\ R\sin\phi\sin\theta \\ R\cos\phi \end{bmatrix}$$

$$\boldsymbol{r} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

EnKF biased towards Gaussian distributions

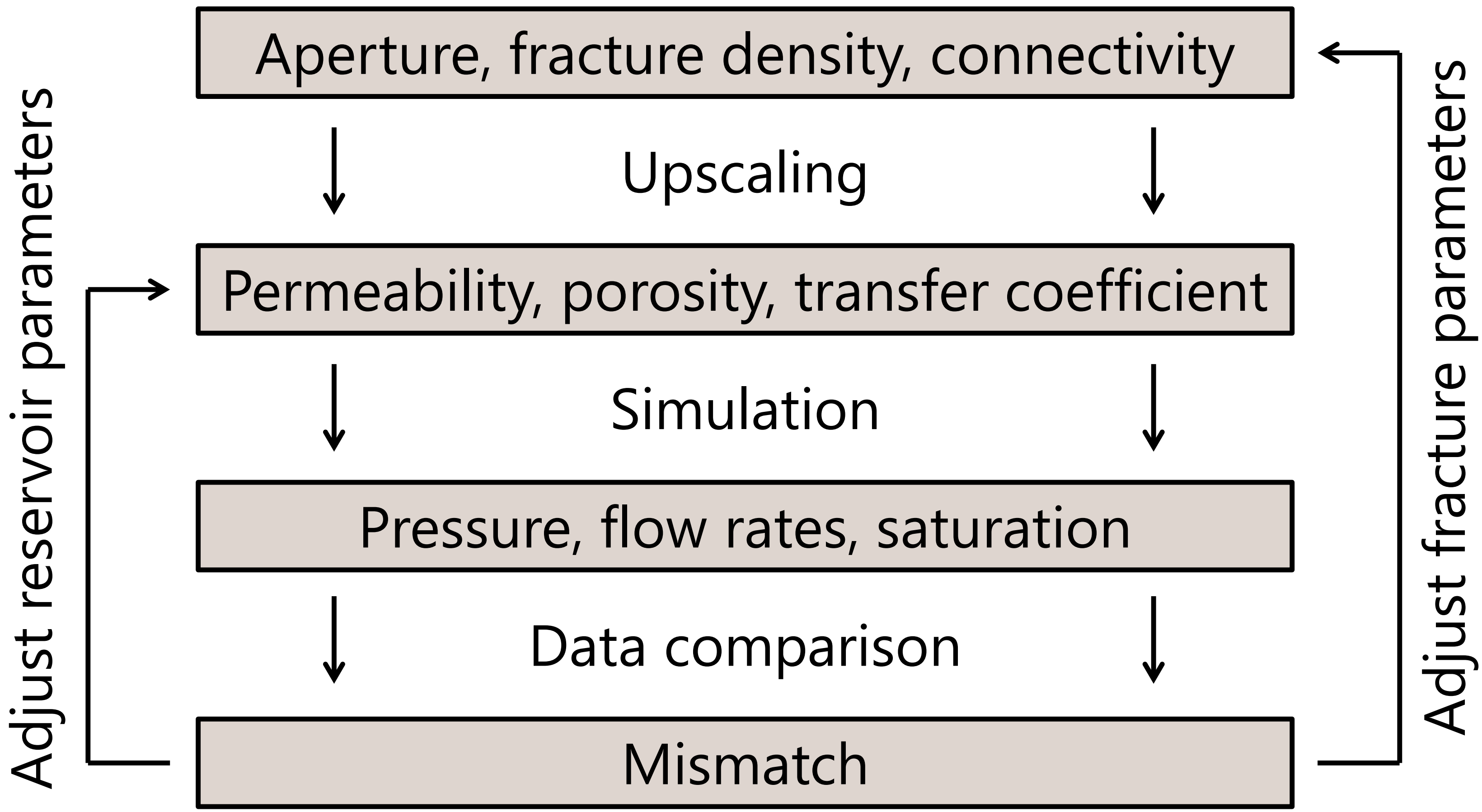


Posterior probability



Correlation

Choice of primary variables



Fracture upscaling

Analytical

- Fast solution
- Derivatives easily obtained
- Requires macroscopic homogeneity
- May not be applicable to all geometries

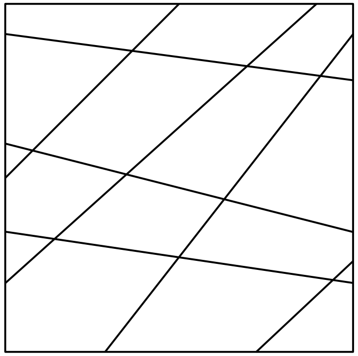
Numerical

- Computationally expensive
- Technically difficult
- Potentially accurate
- Flexible formulation

Analytical fracture upscaling

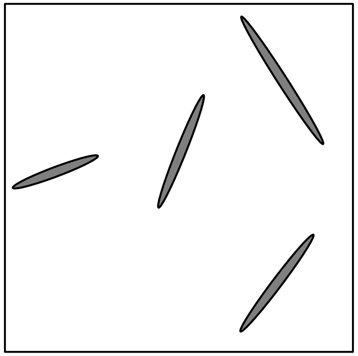
Layer-based

- Fractures are modeled as infinitely extending thin layers
- Modifications are applied to account for partial connectivity



Inclusion-based

- Fractures are modeled as infinitely separated inclusions
- Modifications are applied to account for fracture interaction



Layer-based fracture upscaling

- Permeability

$$\mathbf{K} = \mathbf{K}_{mat} + f \sum_{i=1}^{N} \frac{a^3 \rho_i}{12} \left(\boldsymbol{I} - \mathbf{n}_i^\top \mathbf{n}_i \right)$$

- Porosity

$$\phi = a \sum_{i=1}^{N} \rho_i$$

- Transfer coefficient

$$\sigma = 4 \, \mathrm{Tr}(\mathbf{R}^\top \mathbf{R})$$

$$\mathbf{R} = \sum_{i=1}^{N} \rho_i \, \mathbf{n}_i^\top \mathbf{n}_i$$

A simple example

- Randomly oriented, infinitely extending fractures
- No permeability within the matrix
- Exact upscaling assumed

$$K = \frac{a^3 \rho}{18}$$

$$\phi = a\rho$$

$$\sigma = \frac{4}{3}\rho^2$$

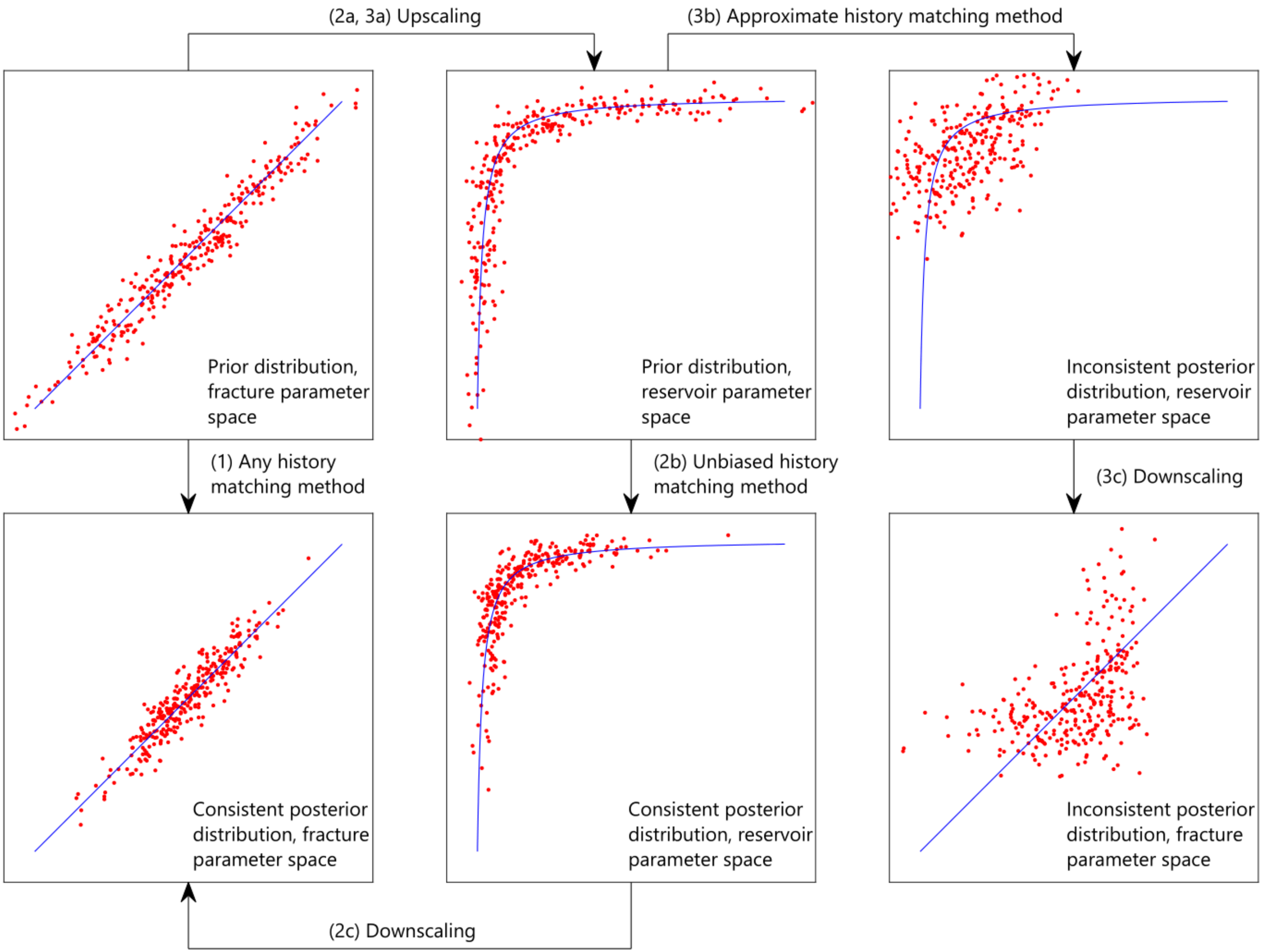
- Single simulation grid block
- The inverse upscaling transform is well-defined

A simple example

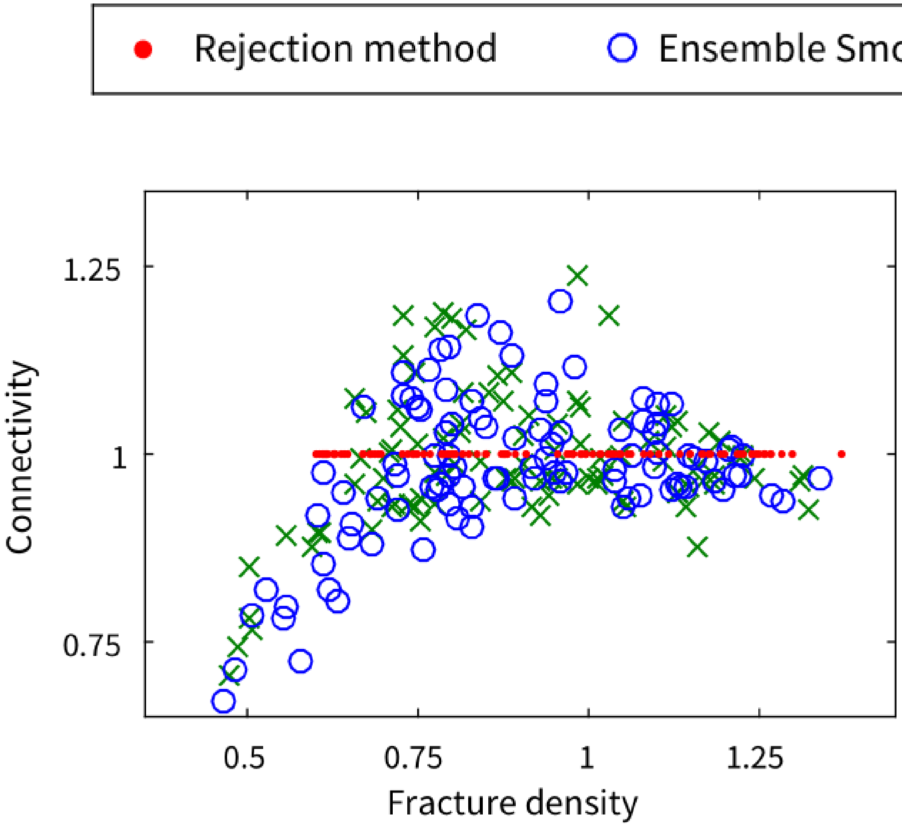
- Uniform distribution for the prior data
- Measured data has gaussian noise

	Prior mean (μ)				Prior scatter (s)				Measurement	
	a	A	δ	R	a	A	δ	R	K_m	SD(ϵ)
Case 1	0.2 mm	$1\,\mathrm{m}^{-1}$	0	∞	0.04 mm	$0.4\,\mathrm{m}^{-1}$	0	0	300 mD	30 mD
Case 2	0.2 mm	$1\,\mathrm{m}^{-1}$	0	5 m	0.04 mm	$0.4\,\mathrm{m}^{-1}$	0	0	300 mD	30 mD
Case 3	0.2 mm	$1\,\mathrm{m}^{-1}$	0	5 m	0.08 mm	$0.8\,\mathrm{m}^{-1}$	0	0	300 mD	100 mD
Case 4	0.2 mm	$1\,\mathrm{m}^{-1}$	0	5 m	0.04 mm	$0.4\,\mathrm{m}^{-1}$	0.1	0	300 mD	30 mD
Case 5	0.2 mm	$1\,\mathrm{m}^{-1}$	0	5 m	0.08 mm	$0.8\,\mathrm{m}^{-1}$	0.1	0	300 mD	100 mD

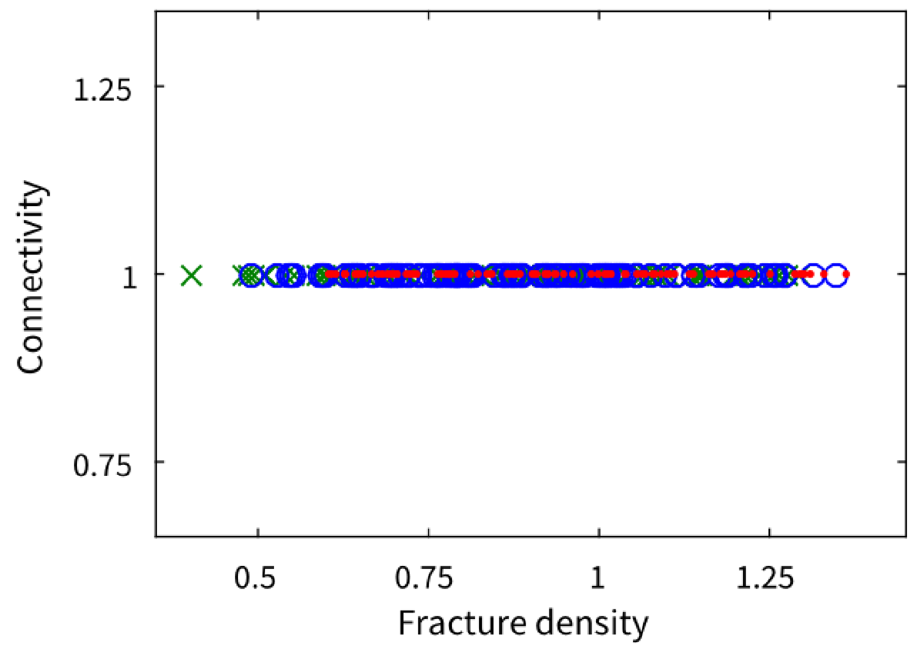
Three ways to get a history matched model



Post-analysis correlations



Reservoir parameters



Fracture parameters

Linear fracture upscaling

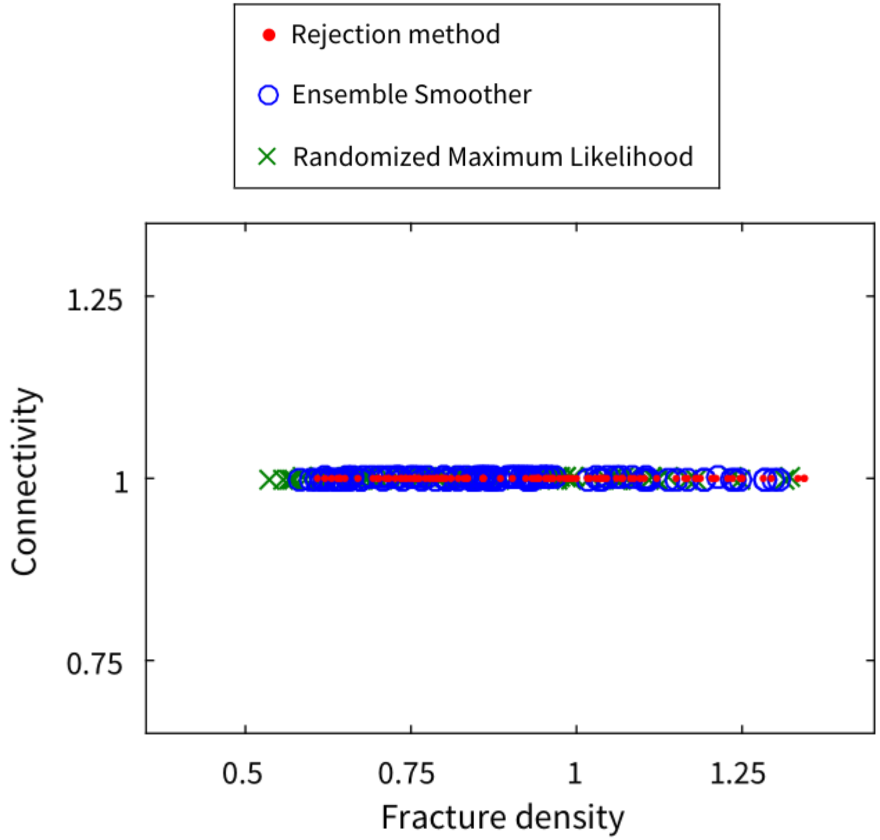
$$\ln K = \ln \frac{a^3 \rho}{18}$$

$$\ln \phi = \ln a\rho$$

$$\ln \sigma = \ln \frac{4}{3}\rho^2$$

Using log of the parameters as primary variables

Upscaling transformation is linear, and connectivity is preserved



Fractures of finite size

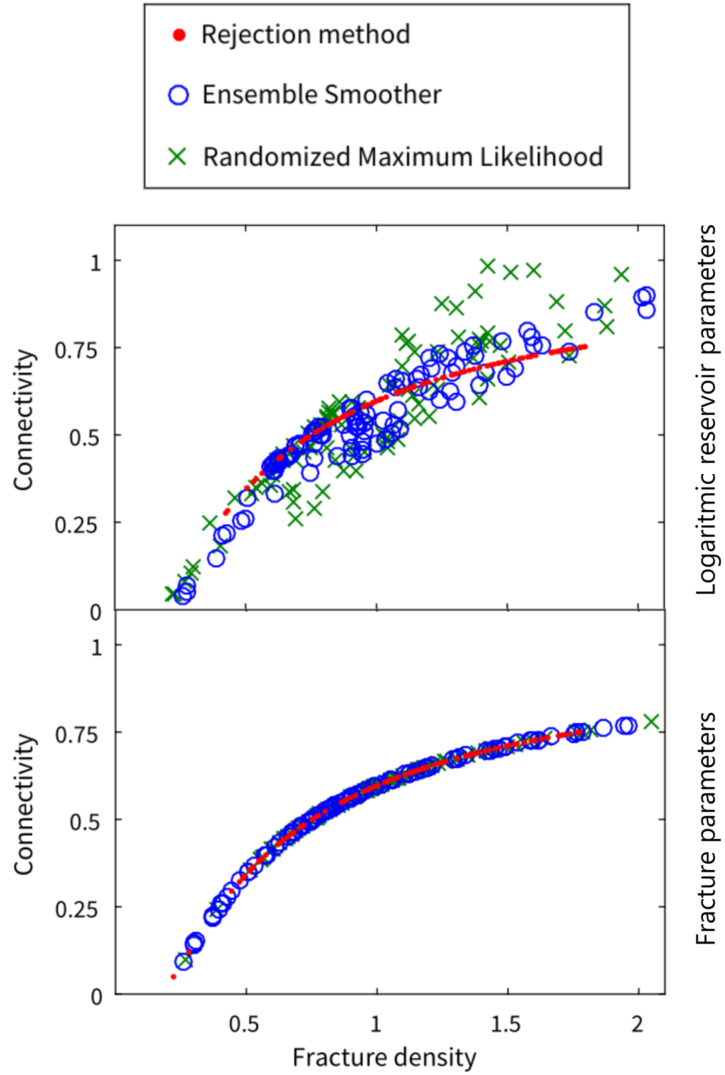
$$\ln K = \ln f \frac{a^3 \rho}{18}$$

$$\ln \phi = \ln a\rho$$

$$\ln \sigma = \ln \frac{4}{3} \rho^2$$

Connectivity f is calculated using a method of Mourzenko et al. (2011)

Upscaling transformation is nonlinear despite using logarithms

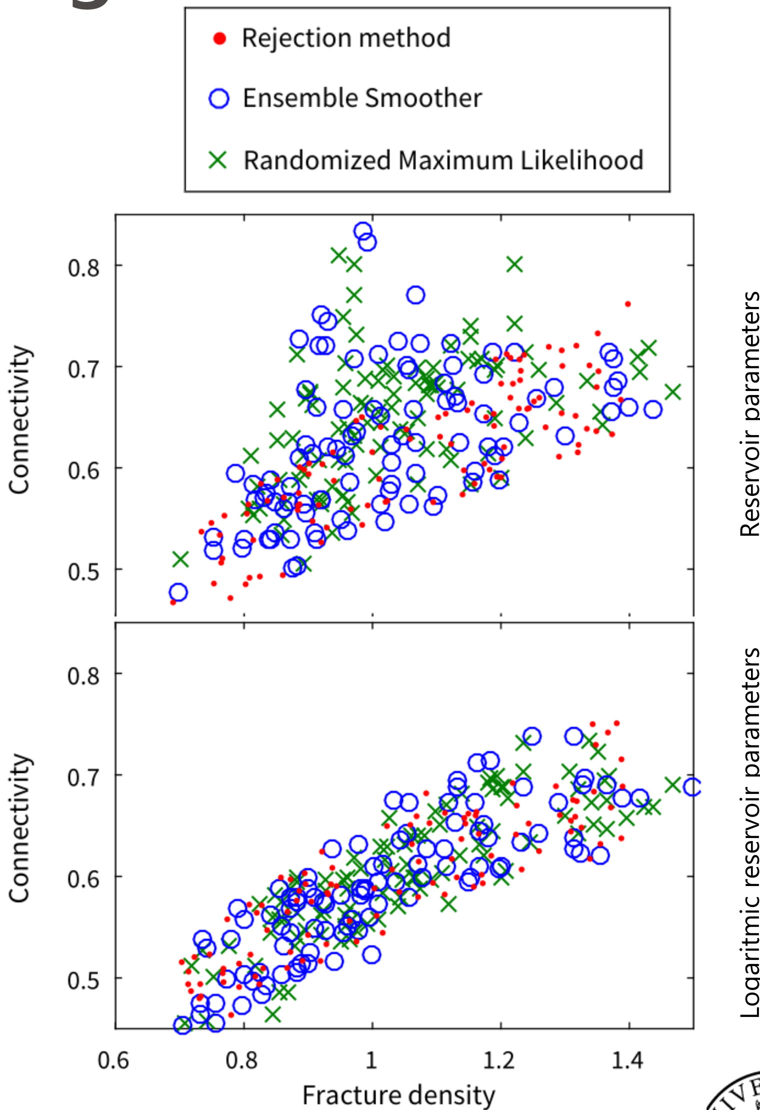


Effects of inexact upscaling method

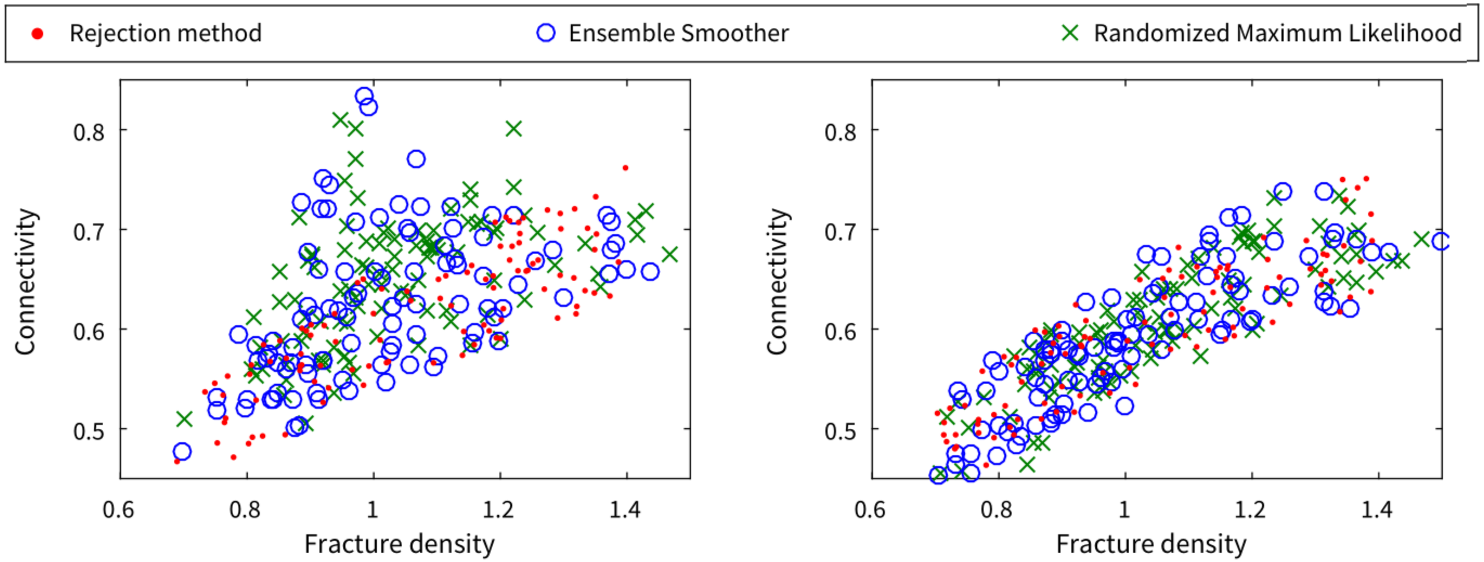
$$\ln K = \ln(1+\delta) f \frac{a^3 \rho}{18}$$

$$\ln \phi = \ln a\rho$$

$$\ln \sigma = \ln \frac{4}{3}\rho^2$$



Effects of inexact upscaling method



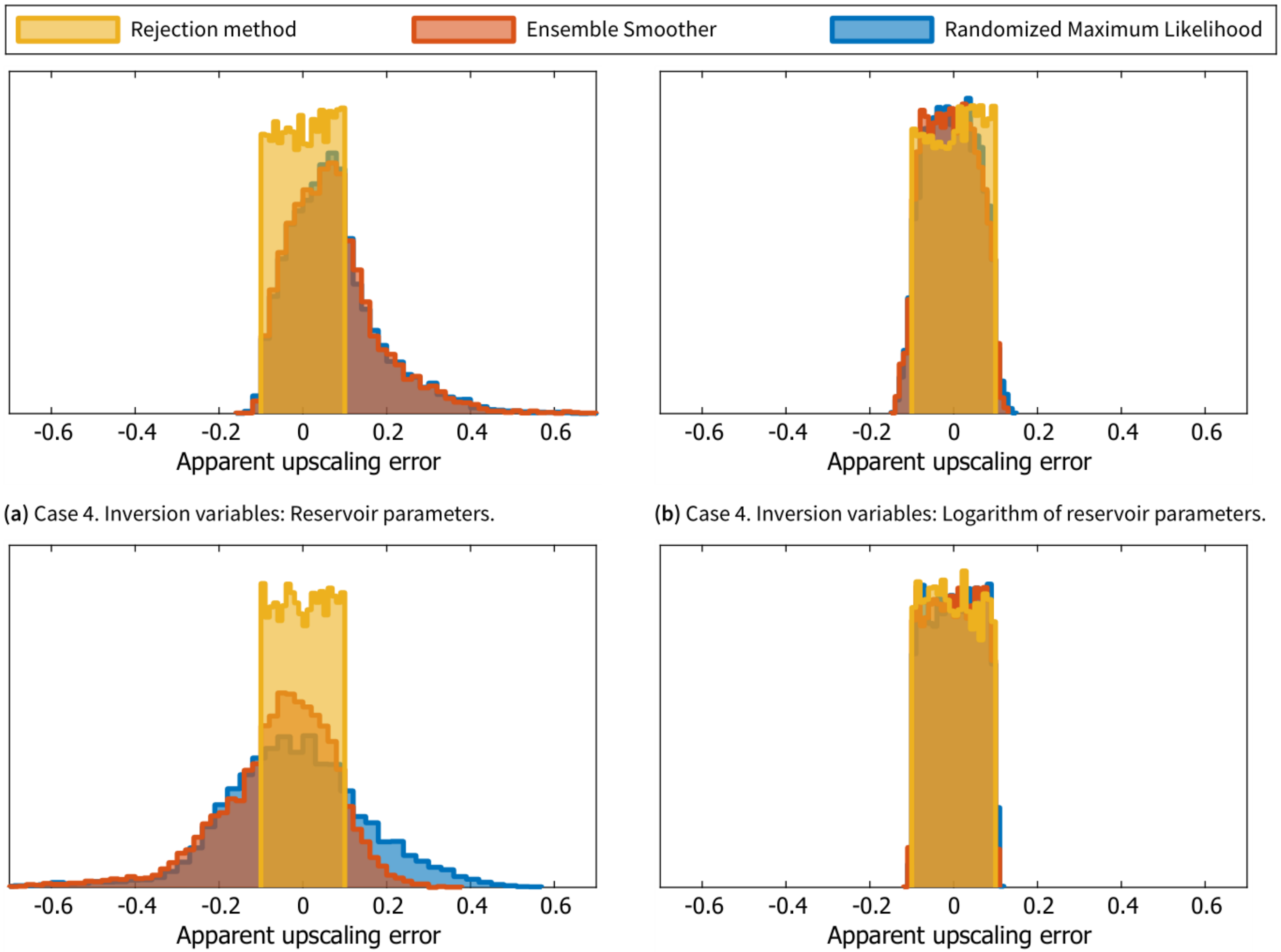
(a) Case 4. Inversion variables: Reservoir parameters.

(b) Case 4. Inversion variables: Logarithm of reservoir parameters.

(c) Case 5. Inversion variables: Logarithm of reservoir parameters.

(d) Case 5. Inversion variables: Logarithm of fracture parameters.

Effects of inexact upscaling method



(a) Case 4. Inversion variables: Reservoir parameters.

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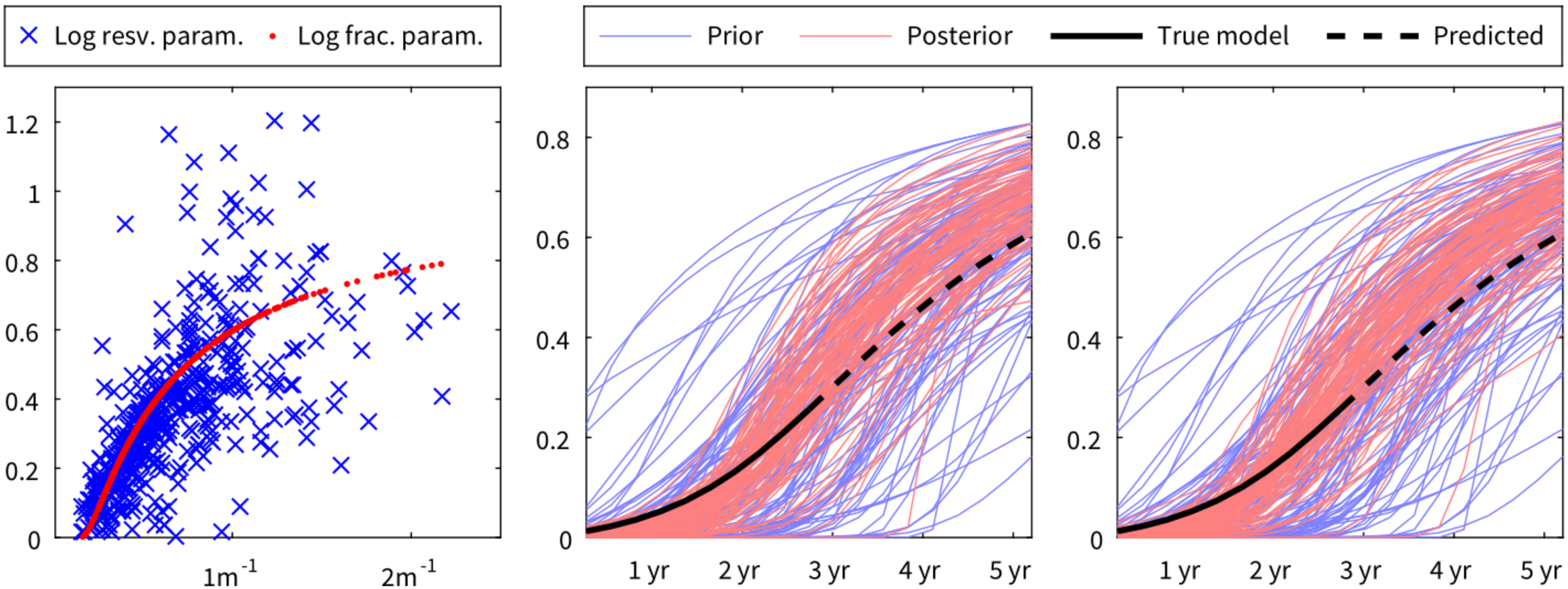
(c) Case 5. Inversion variables: Logarithm of reservoir parameters.

(d) Case 5. Inversion variables: Logarithm of fracture parameters.

Does it matter for prediction?

- Quarter-of-five-spot problem
- Fracture parameters spatially correlated
  - Gaussian spatial covariance model
  - Correlation length ½ of domain size
- Water injection, water-wet reservoir
- Constant injection rate, constant production pressure
- Assimilated data:
  - Volume production rate
  - Injection pressure
  - Water cut

Does it matter for prediction?



(a) Fracture connectivity vs. density, for 500 random grid blocks in the posterior ensemble. Legend indicates the choice of inversion variables.

(b) Prior and posterior water cut data, using logarithm of fracture parameters as inversion variables.

(c) Prior and posterior water cut data, using logarithm of reservoir parameters as inversion variables.

Concluding remarks

- Using **upscaled parameters** as primary variables during inversion, may generate parameter distributions that are **inconsistent** with the underlying fracture description

- The effect is most clearly seen for **partially connected** fracture networks, for which there exists an **accurate upscaling** relationship

- The problem can be avoided by using **fracture parameters** as primary variables, and include upscaling as an integral part of the history matching workflow

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