The road ahead: the integrated MeProRisk approach:

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www.eonerc.rwth-aachen.de/gge

Acknowledgment to co-authors

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This lecture presents ...

- risk and strategies for minimizing risk
- numerical process modeling as pivotal tool
- the MeProRisk - approach
- sources for reservoir data
- reservoir simulation and methods for estimating rock properties
- two examples: (i) crystalline basement, (ii) sedimentary basin
- visualizing results of 3-D simulations
- optimal experimental design: finding the best location for an exploration borehole
- summary

Risks in Geothermal Exploration

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- Risks in hydro-geothermal exploration and use:
- Drilling risk (loss of equipment in the borehole, loss of borehole)
- Technological risk (borehole, pumps, power plant)
- Productivity risk (temperature and flow rate ◊ T ≥ 75 °C, Q ≥ 40 L s-1)
- Thermal Power: $P_t = (\rho\ c)_f\ Q\ \Delta T$

  Q: Flow rate ($m^3\ s^{-1}$); ΔT: Temperature drop (K);
  $(\rho\ c)_f$ Fluid thermal capacity ($J\ m^{-3}\ K^{-1}$)

- Prediction by numerical reservoir modeling

Work flow in numerical reservoir simulation

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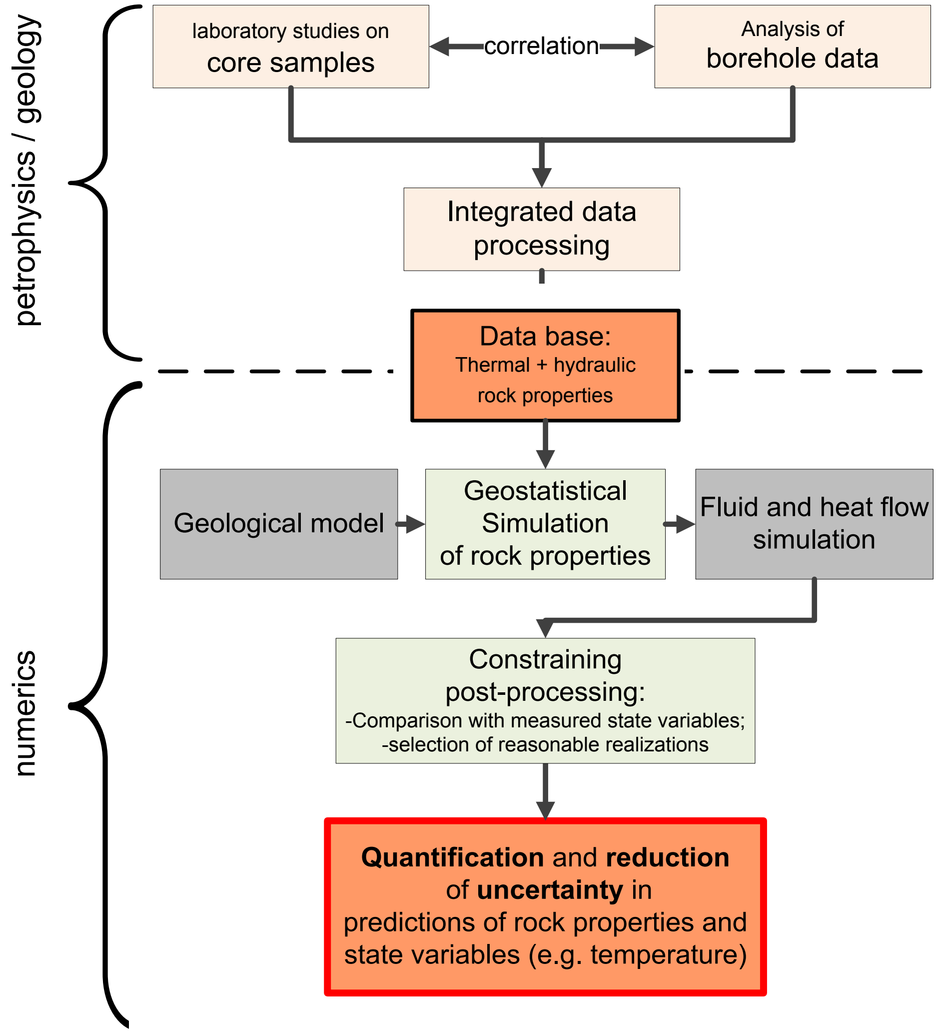
- Provide reliable **structural model**
- Provide data base of **rock properties**
- **Simulate** fluid and heat flow (forward) and estimate rock properties (inverse)
- **Reduce uncertainty of** physical rock properties and thus of **productivity and economic risk**



MeProRisk cooperation

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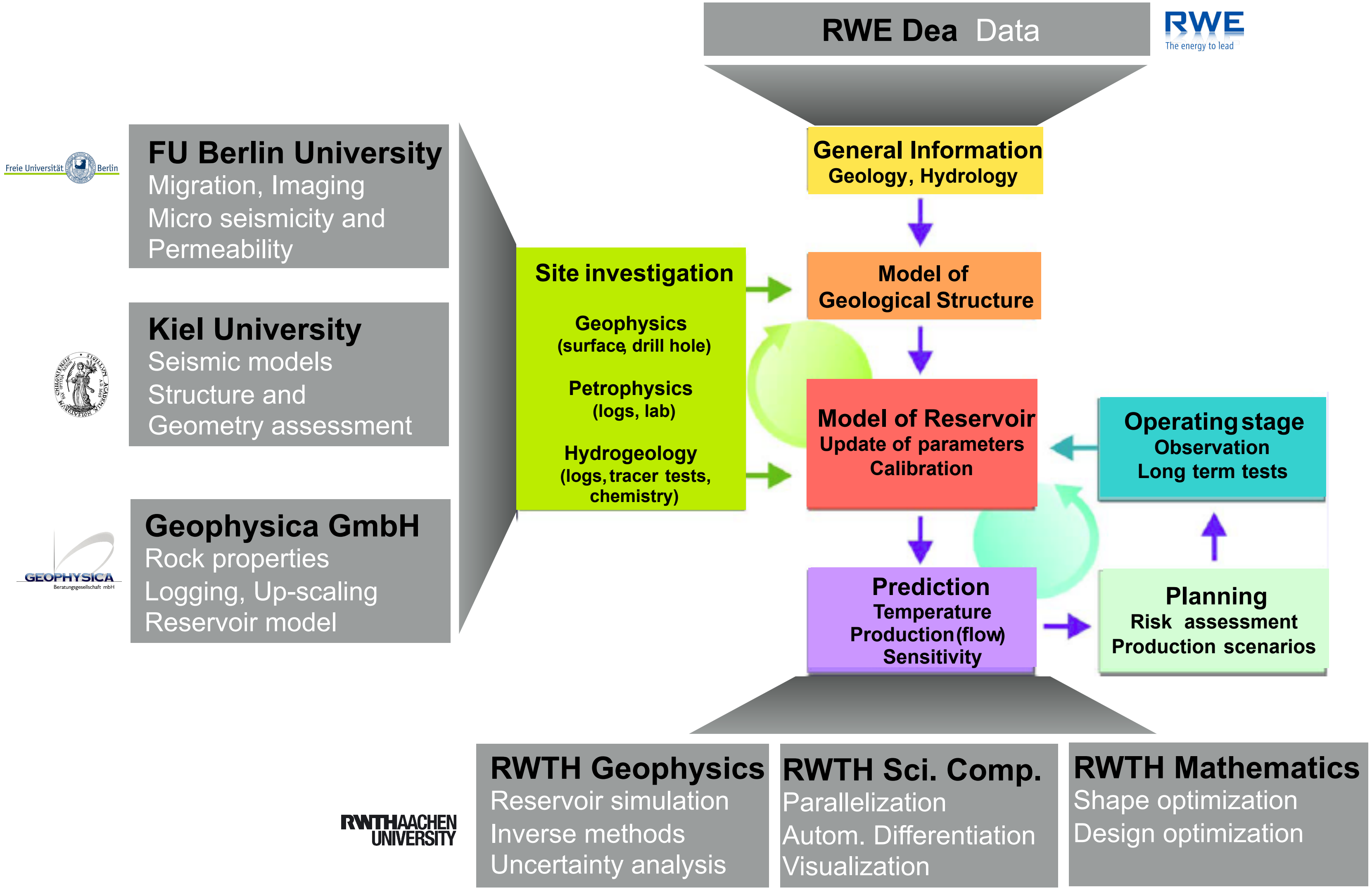

Reservoir rock properties from inversion of borehole logs

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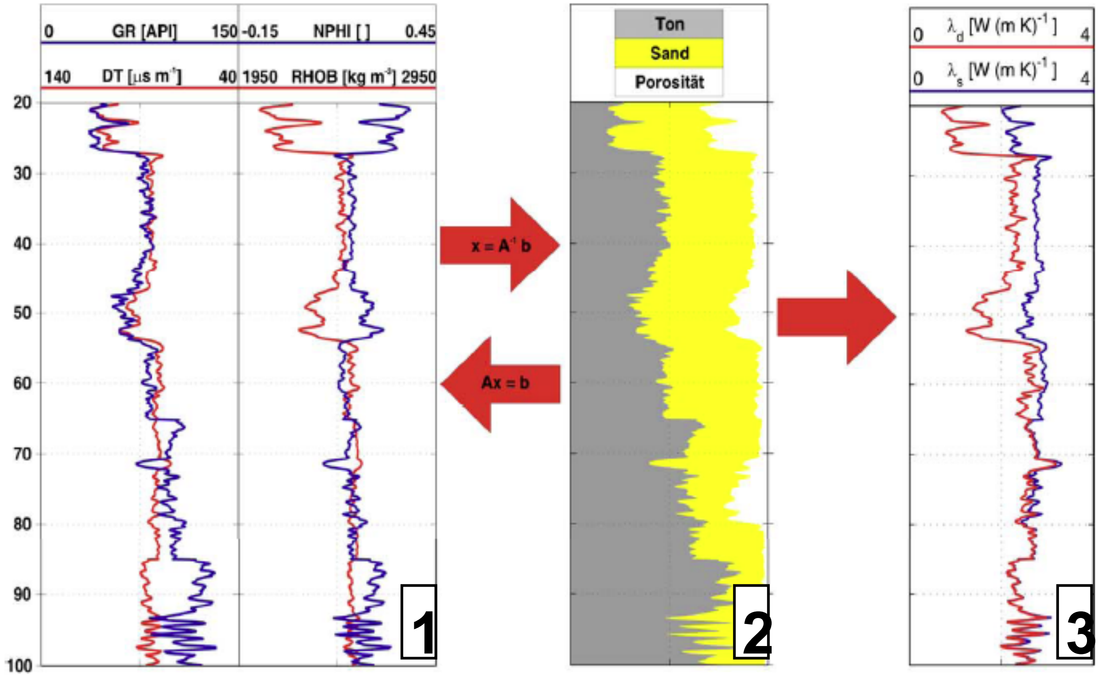


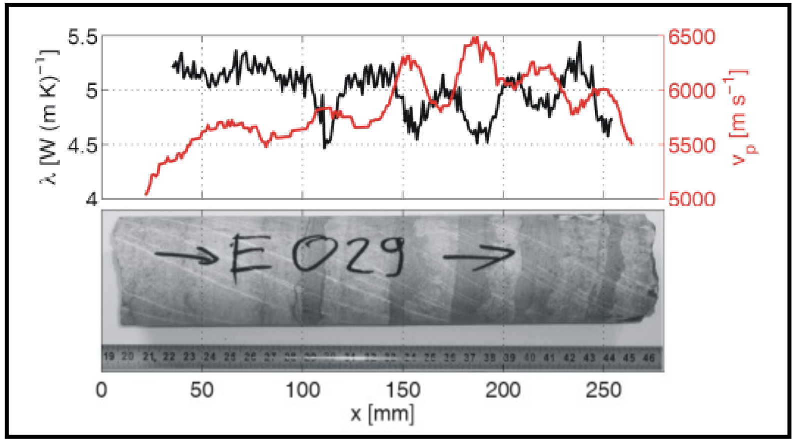
Geophysica GmbH

Integrative statistical petrophysical studies for deriving representative properties for rock types and geological units

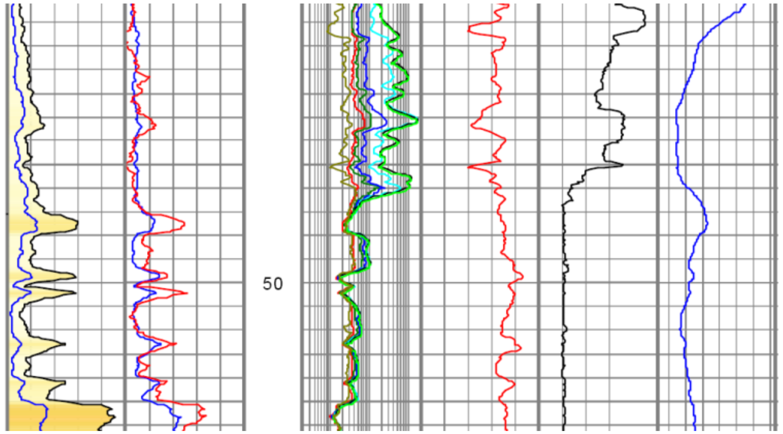
(1) Correlation of rock components and log response
(2) Calculation of volumetric fractions of rock components from log data
(3) Calculation of thermal conductivity using appropriate mixing law

Reservoir rock properties from petrophysical analysis

laboratory studies on core samples ⟵ correlation ⟶ Analysis of borehole data



Example of scanning measurement of thermal conductivity λ and sonic velocity vp (interbedded dolomite - anhydrite).



Example borehole data

+ direct measurements
- selective, not representative

+ allows spatial coverage of geologic units
+ completes vertical profile
- possibly large errors

Statistical reservoir rock property data base

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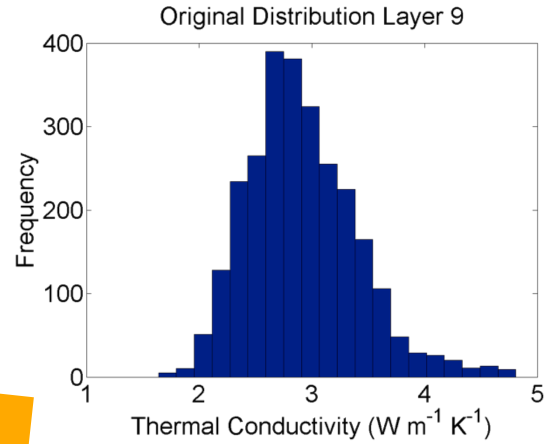
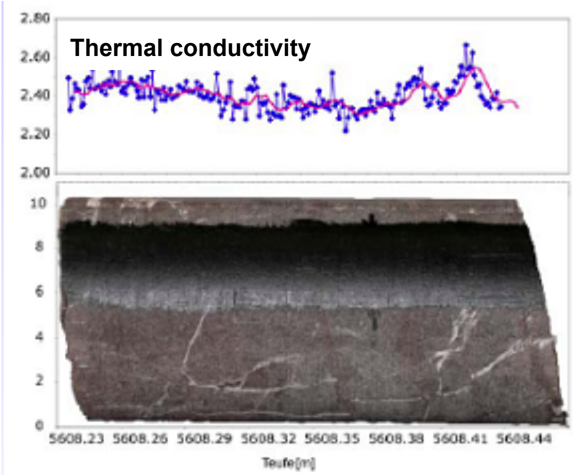
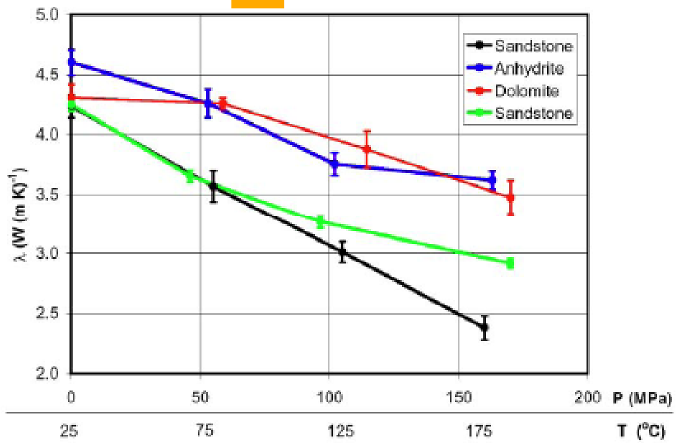
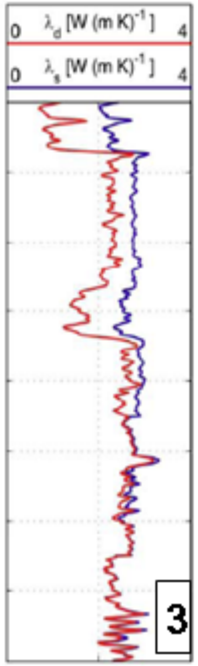
- Probability distribution of rock properties



Geophysica GmbH
Establish rock property data base







Reservoir simulation and prediction

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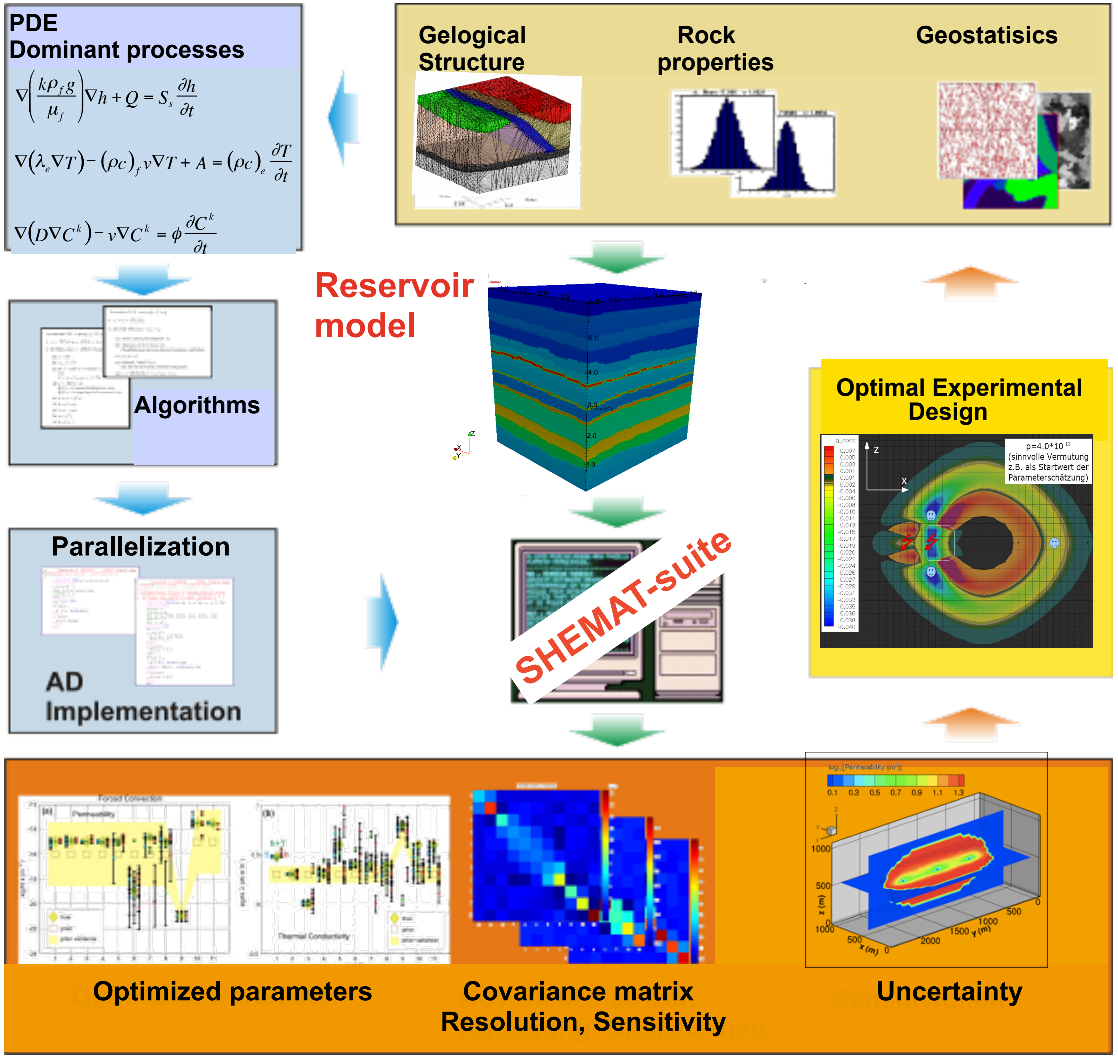

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Reservoir simulation
Shape and design optimization
Uncertainty analysis

Geothermal reservoir simulation – PDEs

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- Fluid flow: $$\nabla\left(k\,\rho_f\,g/\mu_f\right)\nabla h + Q = S_s\frac{\partial h}{\partial t}$$
- Heat transport: $$\nabla\left(\lambda_e\nabla T\right) - \left(\rho c\right)_f v\nabla T + A = \left(\rho c\right)_e\frac{\partial T}{\partial t}$$
- Species transport: $$\nabla\left(D\nabla C^k\right) - v\nabla C^k = \phi\frac{\partial C^k}{\partial t}$$

permeability k [m^2]
porosity ϕ [-]
density (fluid/effective) ρf/e [kg m^{-3}]
fluid dynamic viscosity μf [Pa s]
gravity g [m s^{-2}]
hydraulic head h [m]
specific storage coefficient Ss [m^{-1}]
source term Q [s^{-1}], A [W m^{-3}]
temperature T [°C]
effective thermal conductivity λe [W m^{-1} K^{-1}]
concentration C^k [mmol L^{-1}]
heat capacity (fluid/effective) cf/e [J kg^{-1} K^{-1}]
specific discharge v [m s^{-1}]
dispersion tensor D [m^2 s]

solved by *SHEMAT-Suite,* an advanced version of *SHEMAT* for 3-D forward and inverse simulations

Rath et al. 2006

Methods for Property Estimation

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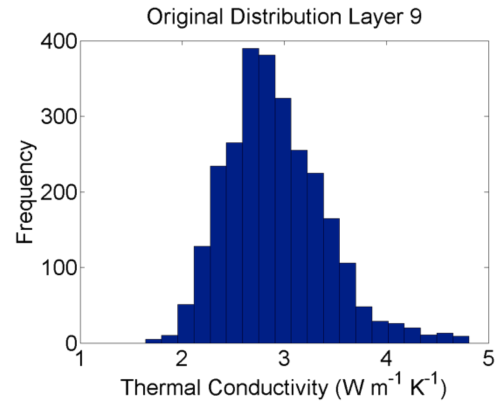
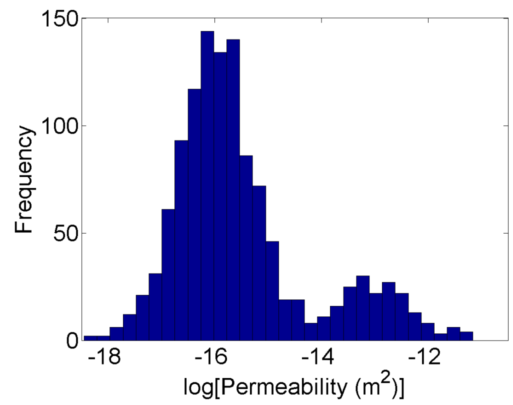
- Bayesian Inversion
  Optimization of an objective function
  (AD technique used to determine the covariance matrix)

$$\Theta = \underbrace{\left(d - g(p)\right)^T C_d^{-1} \left(d - g(p)\right)}_{\text{least squares on parameters}} + \underbrace{\left(p - p_a\right)^T C_p^{-1} \left(p - p_a\right)}_{\text{least squares on data}} = Min\,!$$



- Geostatistical Monte Carlo
  Rock properties assigned randomly to a large number of models according to given histograms



- Ensemble Kalman Filter
  Recursive data assimilation (=comparison of data with simulation prediction and corresponding system adjustment) whenever in time data (and its errors) becomes available

Comparison of Methods: Soultz-sous-Forêts Tracer test

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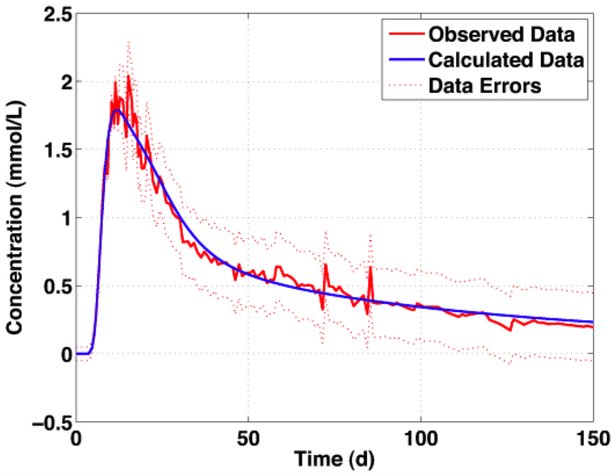
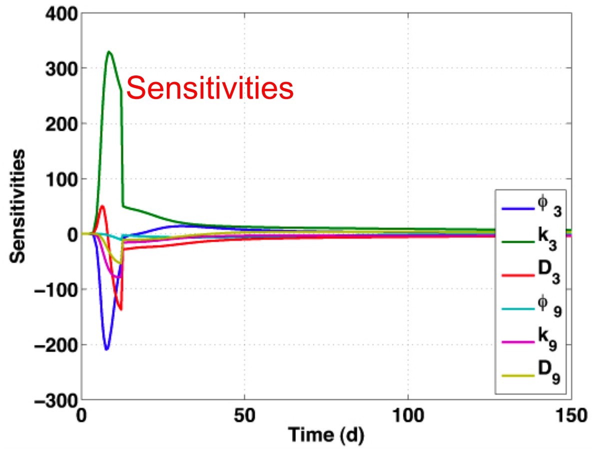
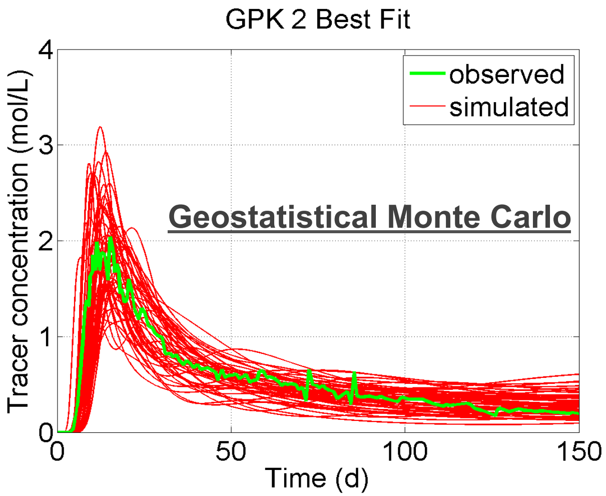
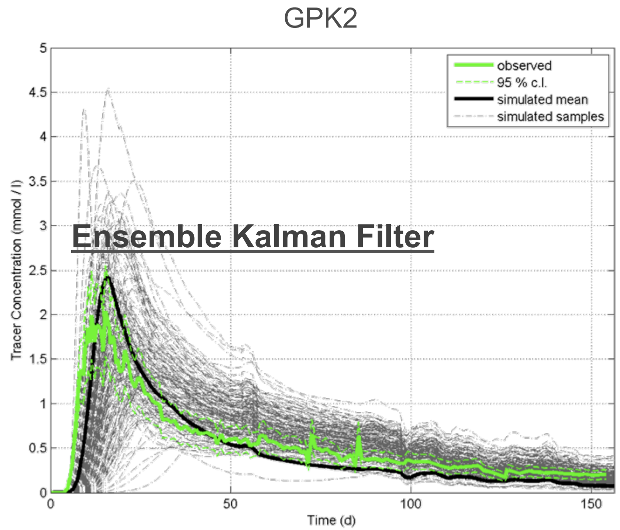


Bayesian Inversion





100 best fits of 5000 realizations



Test Location-Type 1 : Basement Rocks

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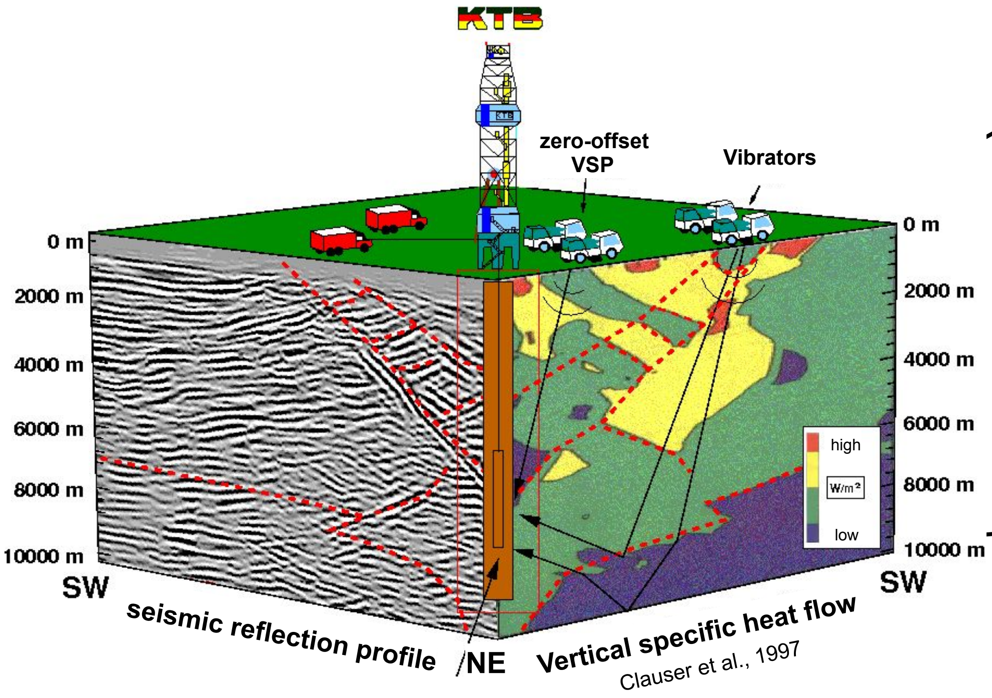
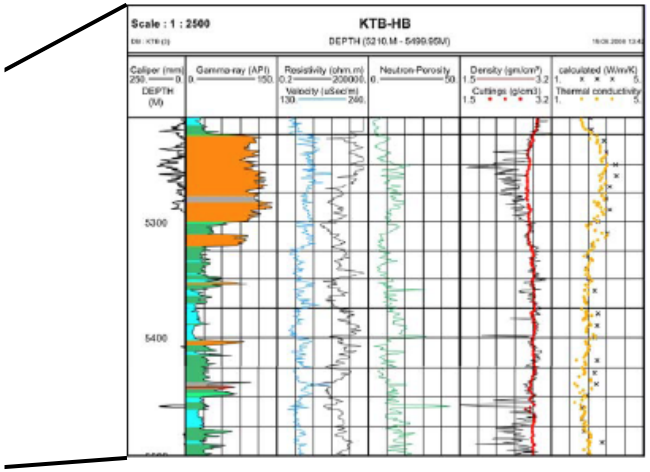
- **Southern German Crystalline Basement**
  - fragmented metamorphic rocks
  - Data from the German Continental Deep Drilling KTB
    Pilot hole: 4000 m, main hole: 9101 m
  - 3-D seismics, long-term hydraulic tests with seismic monitoring, log &core data





KTB – Reservoir Structure and Geometry

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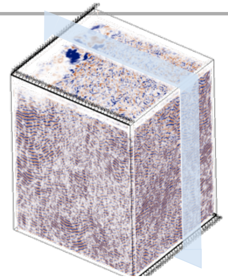
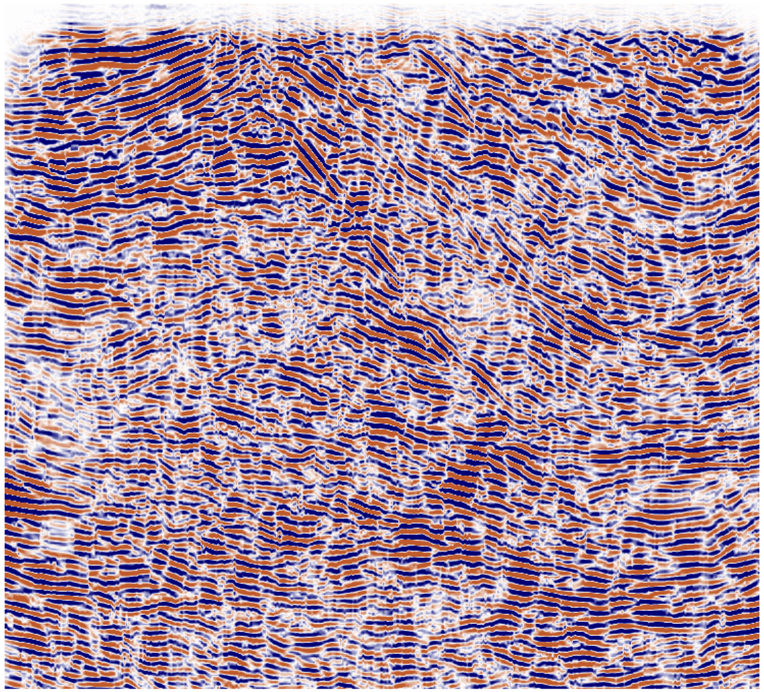
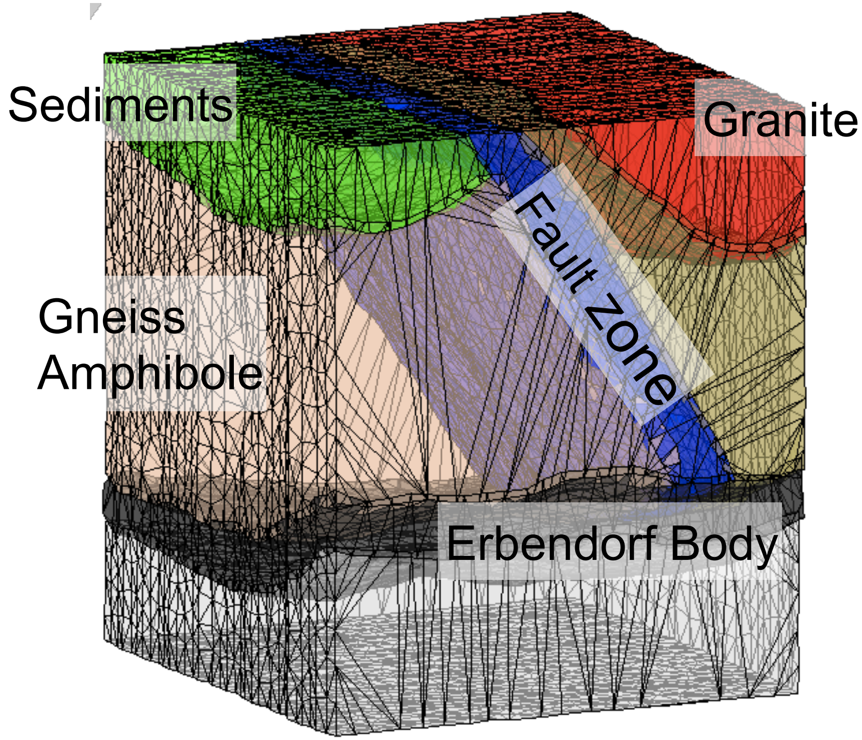


Geological units

Kiel University
Development & application of new filter techniques for structure recognition



Inline 400 - measured



E. Szalaiova, Kiel

Calculation of coherency from eigen-structures of covariance matrices

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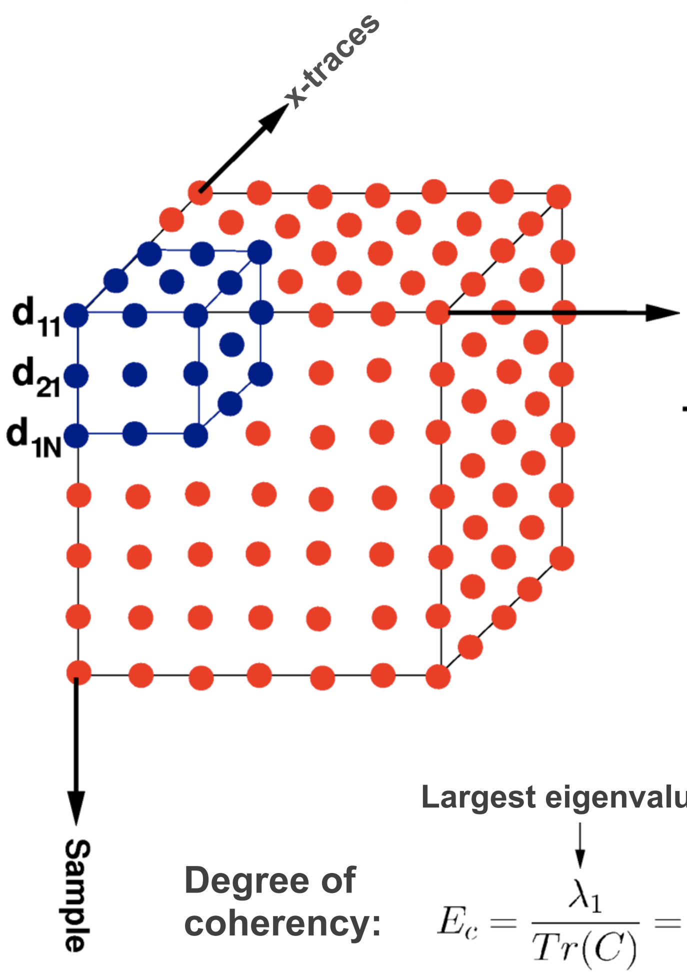

Data matrix

$$D = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1J} \\ d_{21} & d_{22} & \dots & d_{2J} \\ \vdots & \vdots & \vdots & \vdots \\ d_{N1} & d_{N2} & \dots & d_{NJ} \end{bmatrix}$$

Covariance matrix: $C = D^T D$

Largest eigenvalue

Degree of coherency:

$$E_c = \frac{\lambda_1}{Tr(C)} = \frac{\lambda_1}{\sum_{j=1}^{J} c_{jj}} = \frac{\lambda_1}{\sum_{j=1}^{J} \lambda_j}$$

Theory: Gersztenkorn & Marfurt, 1999

KTB – Reservoir Structure and Geometry

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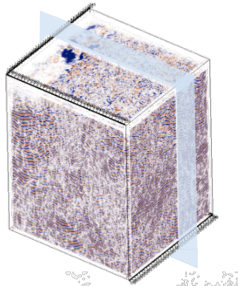
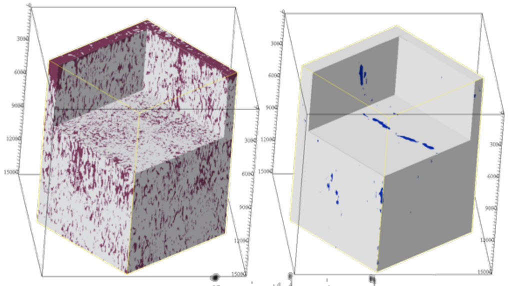
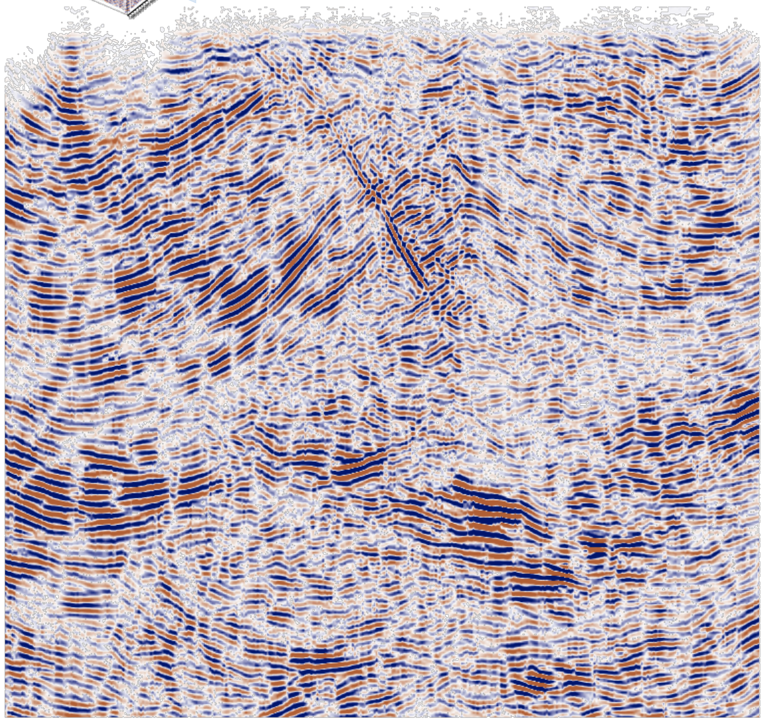


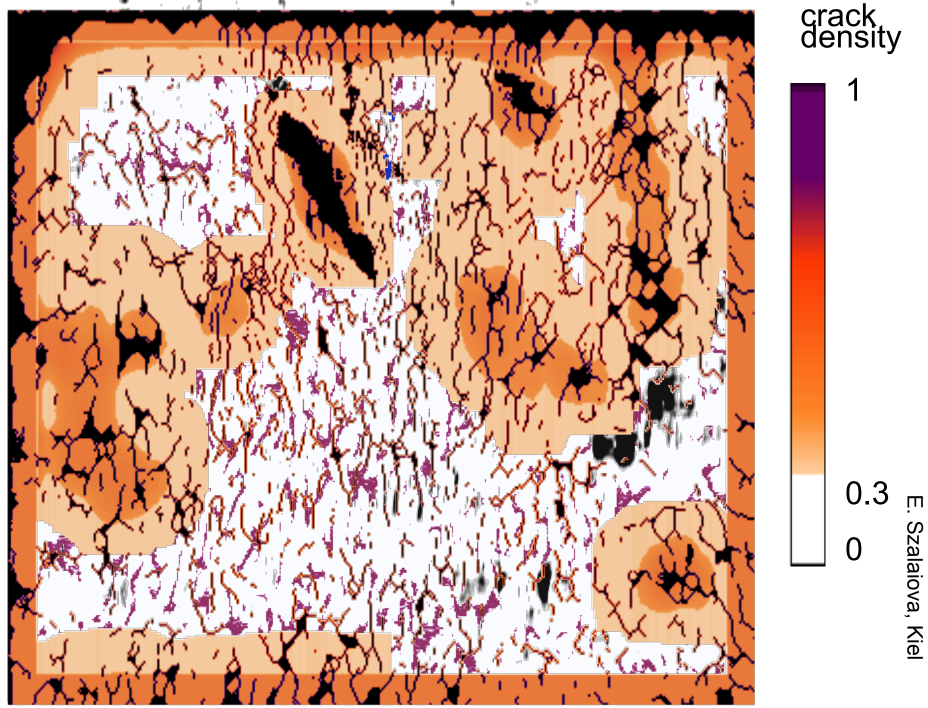
Faults and fissures



Kiel University
Development & application of new filter techniques for structure recognition

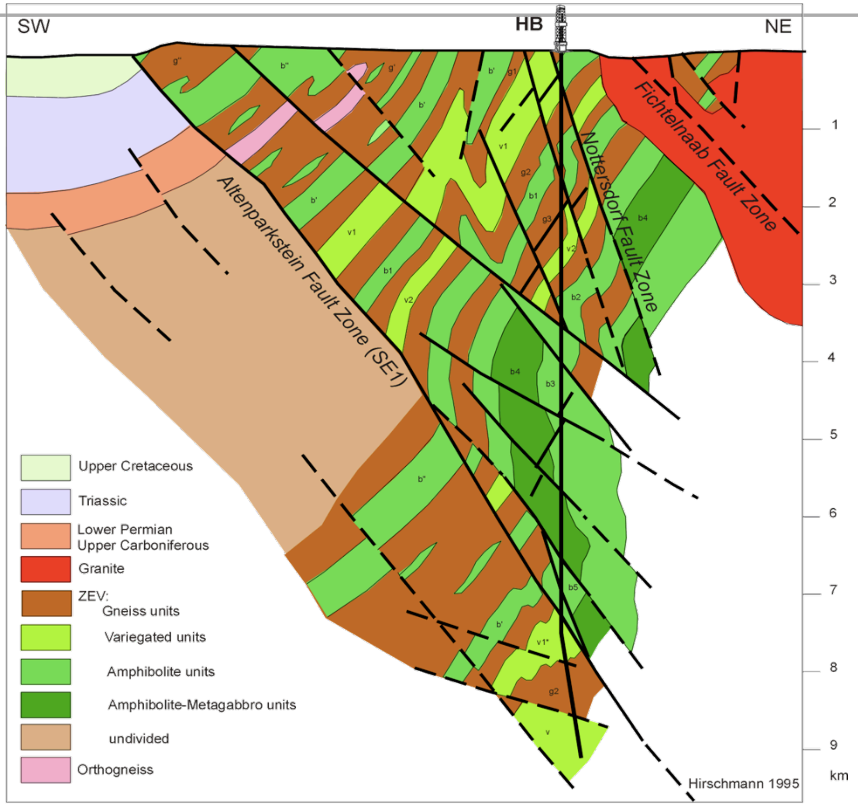


Inline 247 - measured



Inline 247 – faults and fissures

KTB Relation Seismics – Geology



Geologischer SW-NE-Schnitt durch die KTB-Lokation
aus:
Hirschmann, G. (1996): Ergebnisse und Probleme des strukturellen Baues im Bereich der KTB-Lokation. - Geologica Bavarica 101: 37-51

(geringfügig geänderte Farbversion der Abb. 5)

KTB - Reservoir Structure and Geometry

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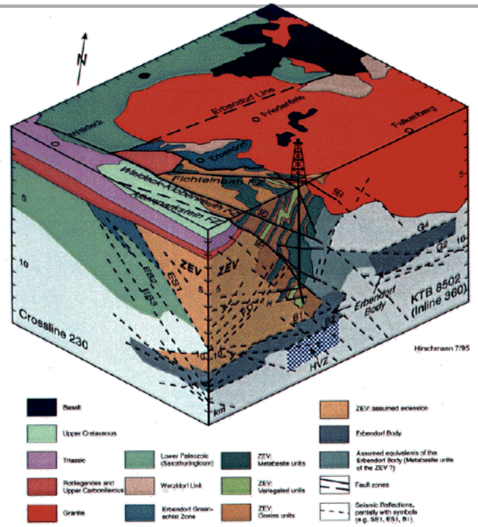
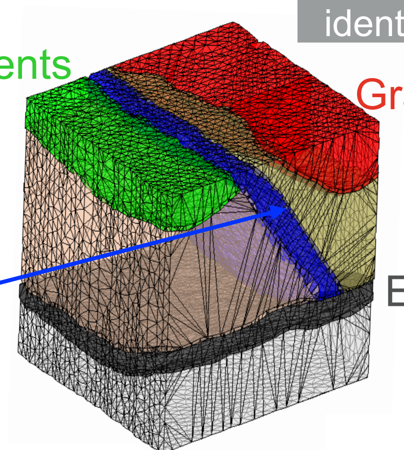
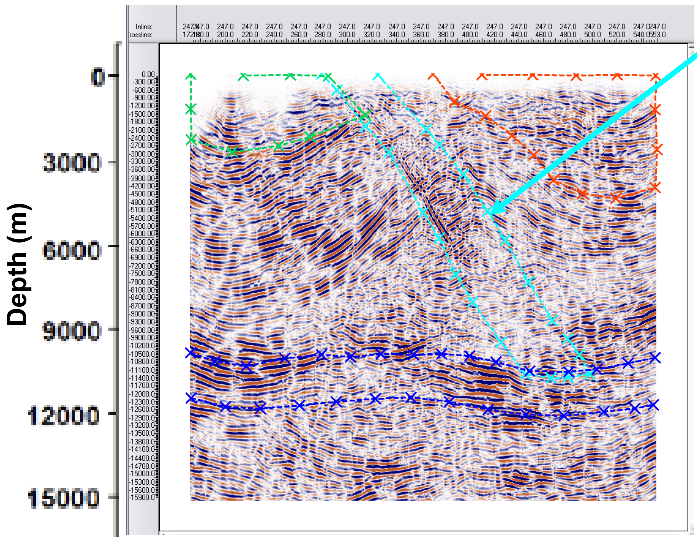


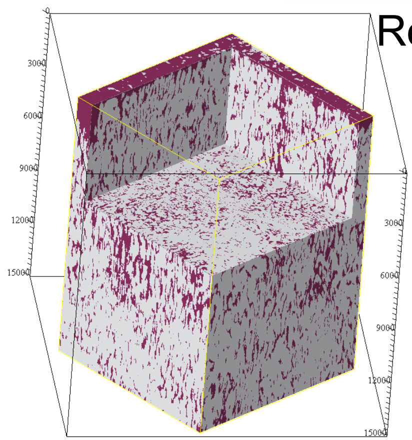
- Test location KTB:
  - Interpretation of seismics

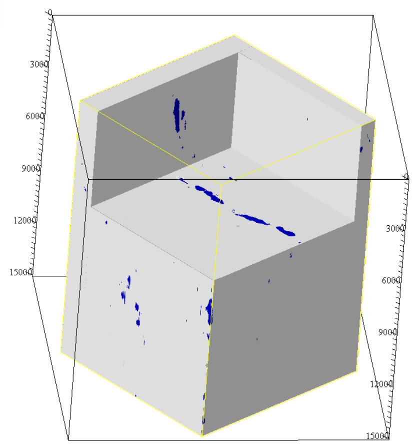
Kiel University
Development & application of new filter techniques for identifying structures



Fault zone




Fissures


Fractures

Iwanowski et al., AGU Fall meeting 2009

KTB - Reservoir Permeability

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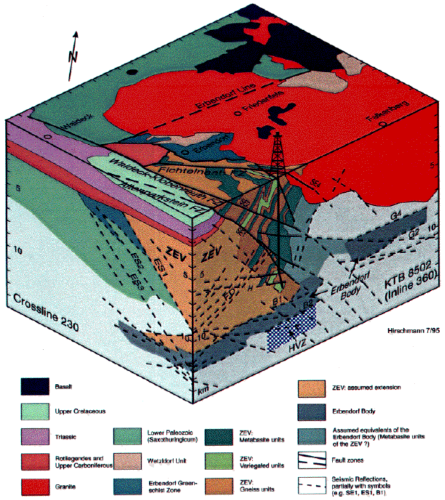
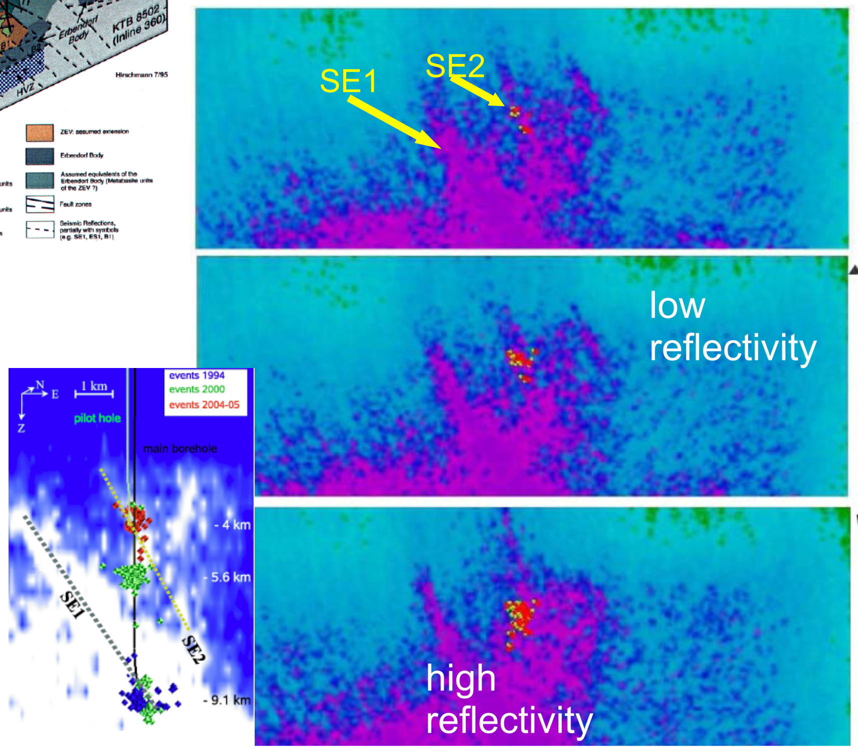
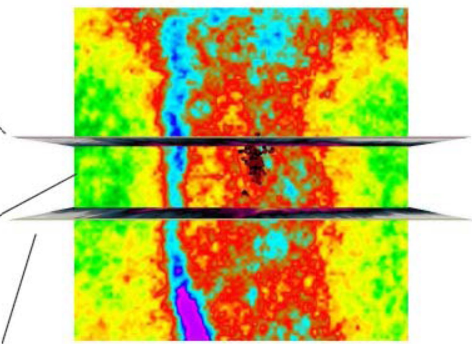
FU Berlin University
Induced seismicity & permeability
Seismic reflectivity & permeability





Vertical slices between 4 km and 7.2 km depth



Horizontal slice at 3.5 km depth

Jaya et al. 2009, EAGE Annual Meeting

- localized micro-tremors

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Flow Simulation – KTB

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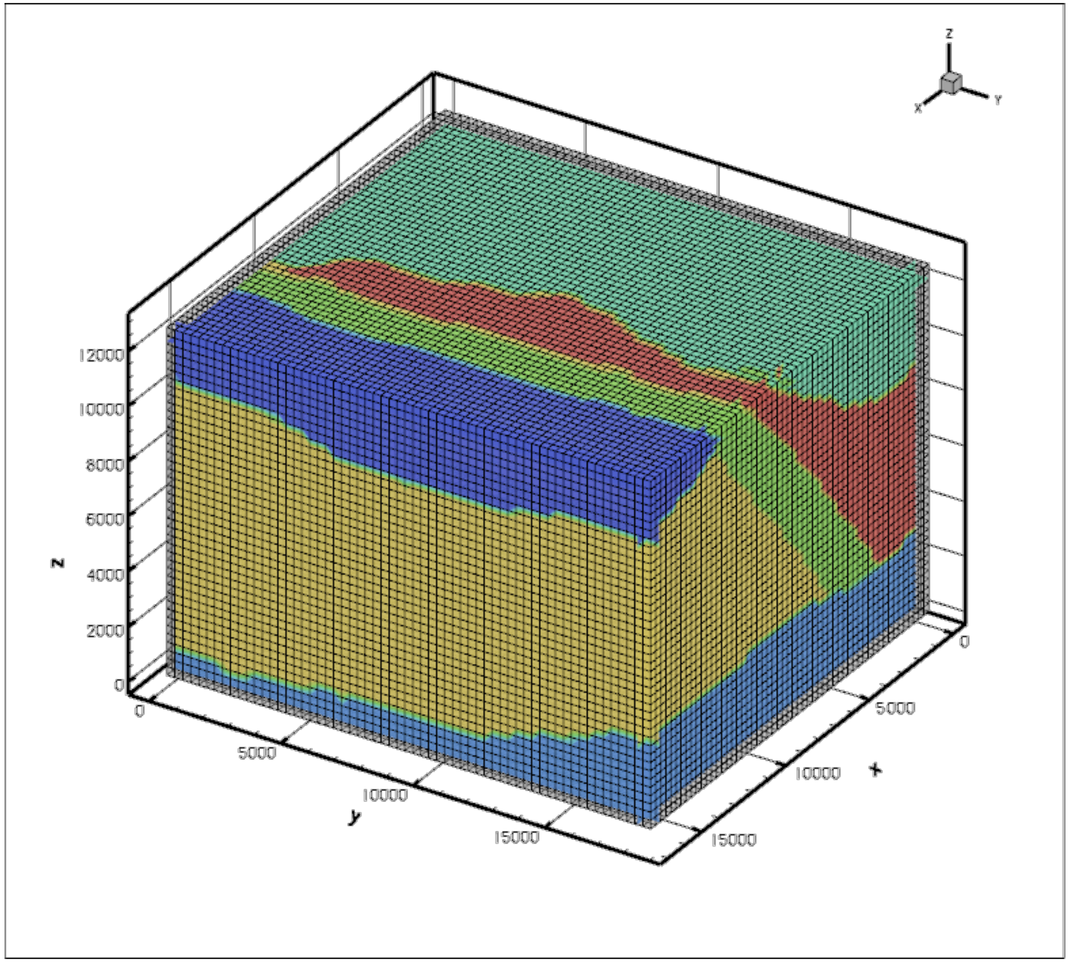


RWTH Aachen & Geophysica GmbH

Assignment of rock properties & development of a hydro-thermal flow model

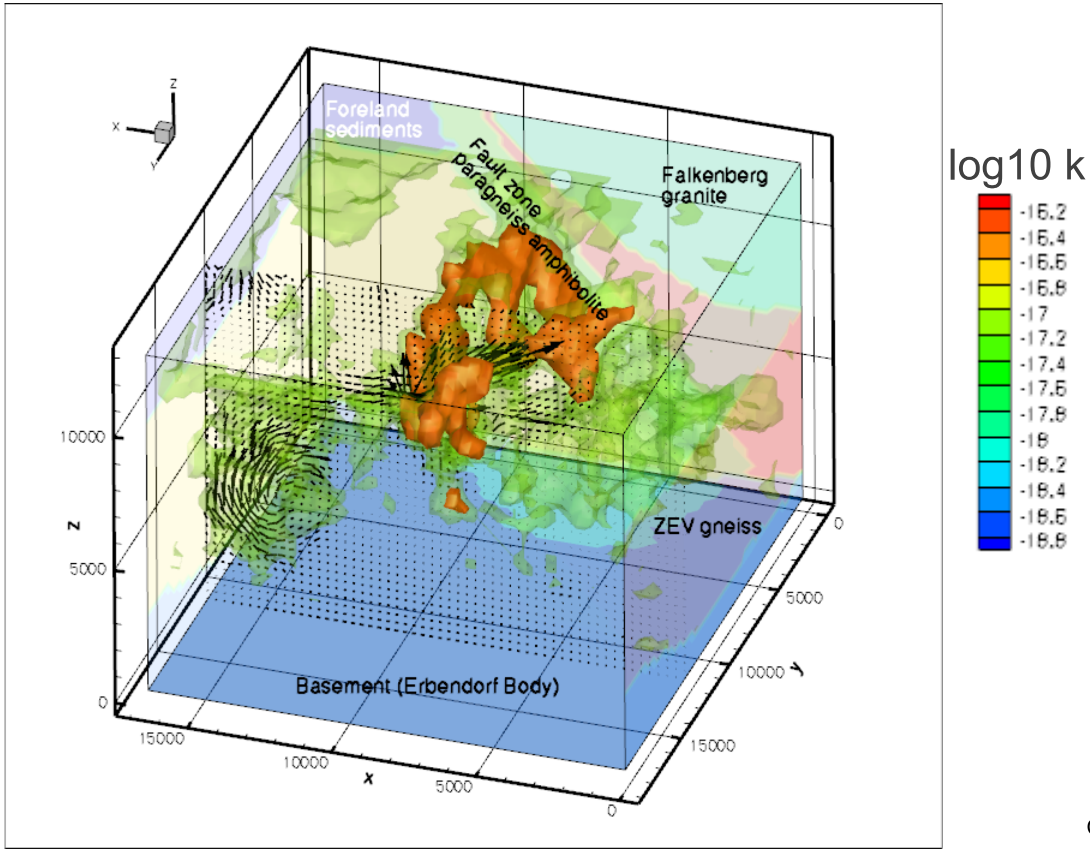
- Grid: 56 × 62 × 43
- T_{top} = 10 °C,
- q_{bottom} = 52 mW m^{-2}
- p_{fluid} top: according to topography
- Rock properties:
  - according to rock type
- Porosity and permeability:
  - according to custom processing of seismics

Flow Simulation – KTB

E.ON Energy Research Center

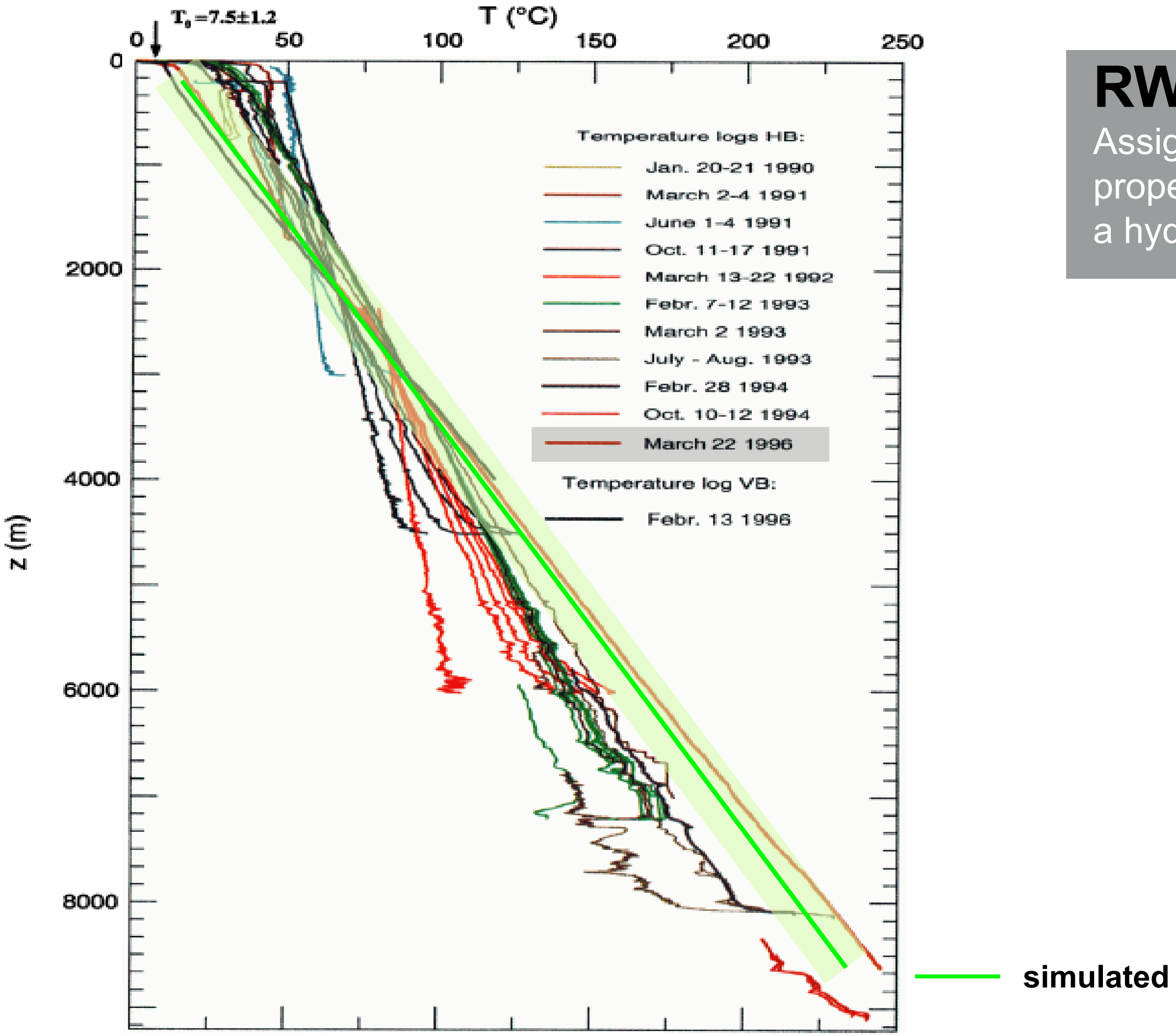
- Units → Rock properties
- Fracure analysis →
  - Rock Permeability
  - Flow model

RWTH Aachen
Assignment of rock properties & development of a hydro-thermal flow model



Christian Kosack

KTB - Temperature Estimate (first results)



RWTH Aachen

Assignment of rock properties & development of a hydro-thermal flow model

Test Location-Type 1 : Basement Rocks

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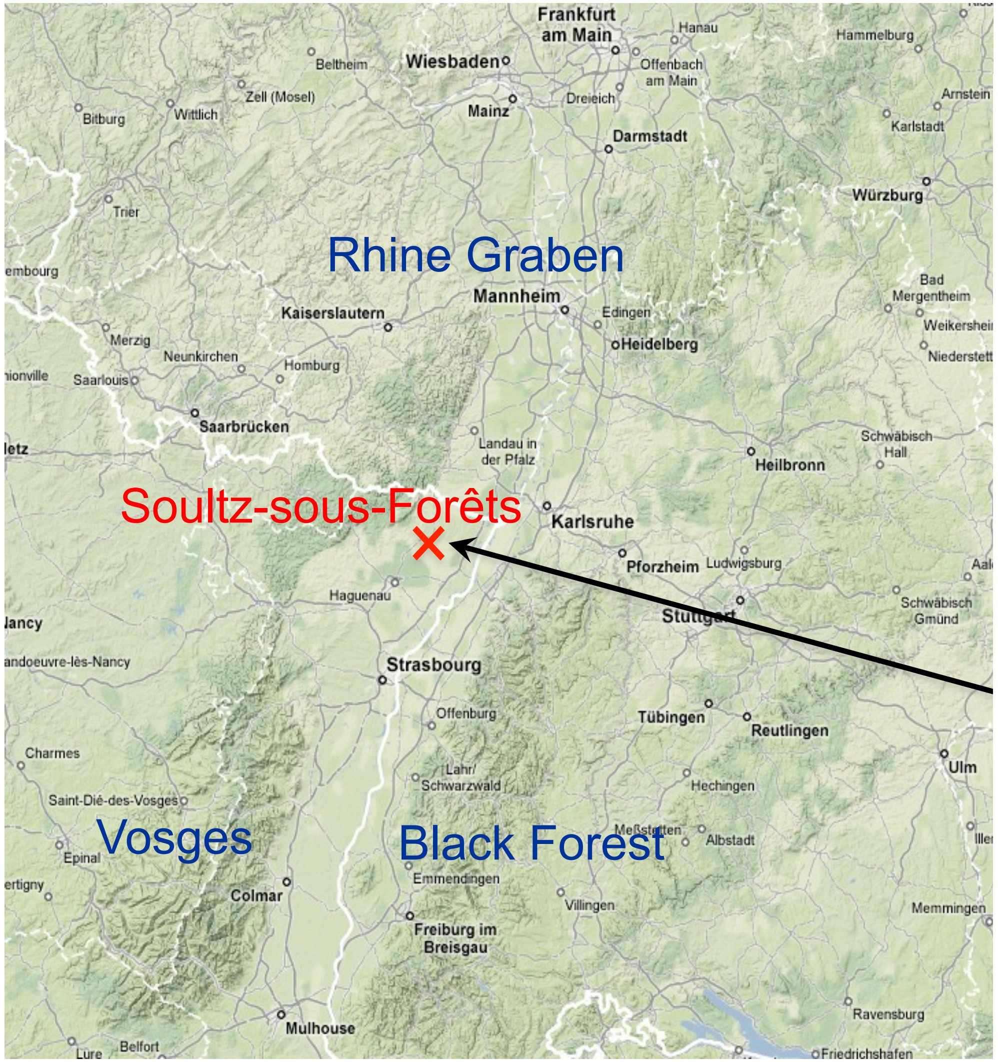
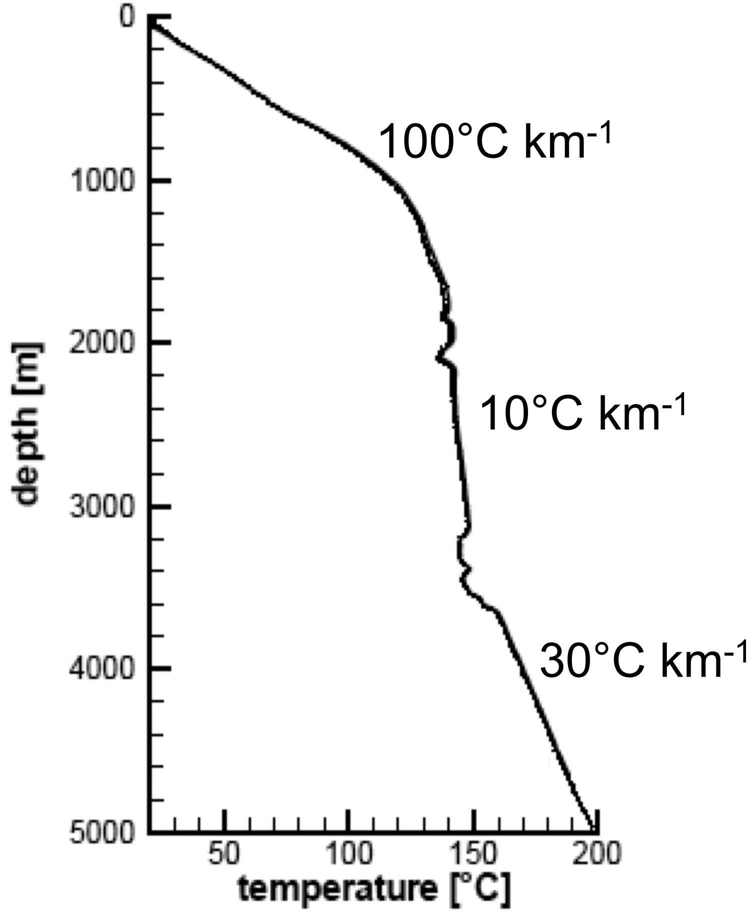
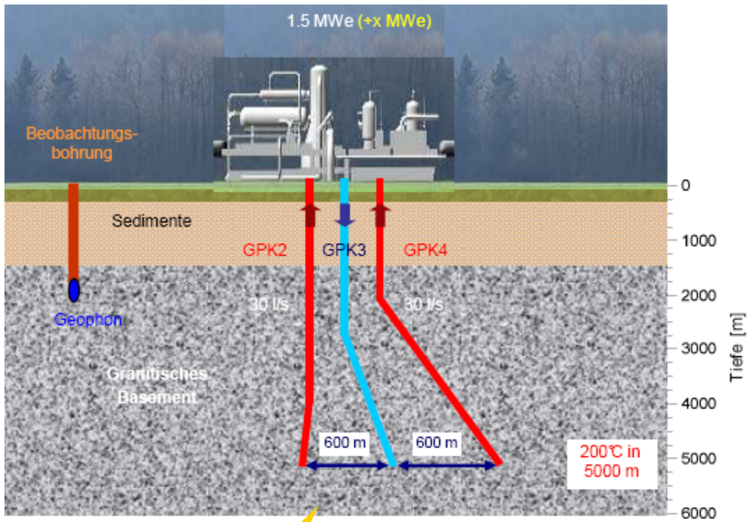


Soultz geotherm

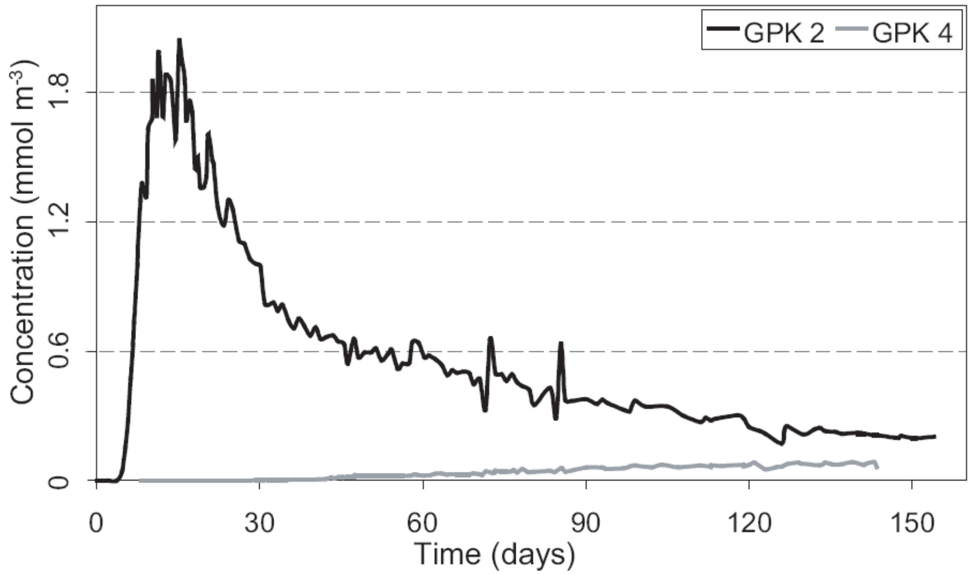


Soultz-sous-Forêts

- Tracer experiment with three boreholes



Stimulated zone



Pump test in 2005:

From central GPK3 to peripheral GPK2 and GPK4

Bayesian Inversion

- Given:
  - *d*: data; p_a: a priori parameters,
  - *g(p):* non-linear system response function relating *p* and *d*

$$\Theta = \left(d - g\left(p\right)\right)^T C_d^{-1}\left(d - g\left(p\right)\right) + \left(p - p_a\right)^T C_p^{-1}\left(p - p_a\right) = Min\,!$$

- Differentiation with respect to parameters yields iteration scheme for improving parameter estimates

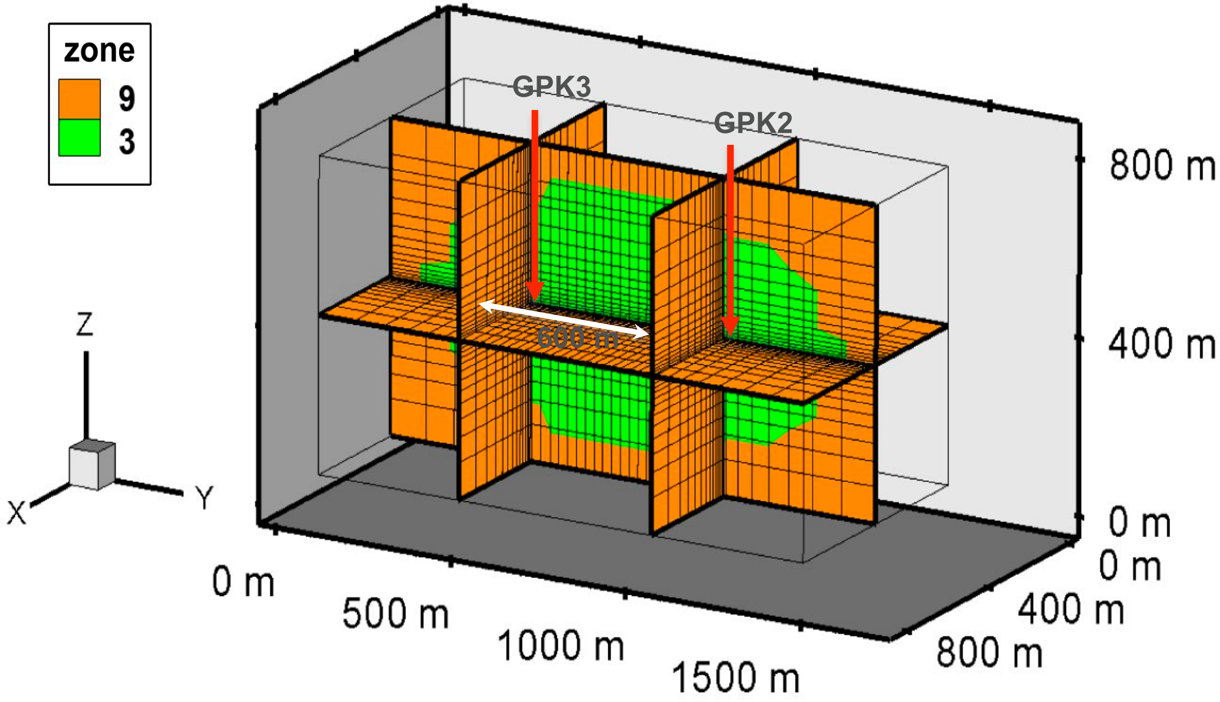
$$p^{k+1} = p_a + \alpha\left(J^T C_d^{-1} J + C_p^{-1}\right)^{-1} \cdot J^T C_d^{-1}\left(d - g\left(p^k\right)\right)$$

- C_d and C_p: data and parameter covariances; $J_{ij} = \frac{\partial g(p)_i}{\partial p_j}$ is the Jacobian

- Result:
  - Parameter set minimizing the residual $r = d - g(p)$ which approximates best the a priori parameters

Soultz-sous-Forêts – Bayesian Inversion

- Data: Recorded Injection and production flow rate
- Properties to estimate:
  - Porosity ϕ
  - Permeability k
  - Dispersion length α_D



Soultz-sous-Forêts – Bayesian Inversion

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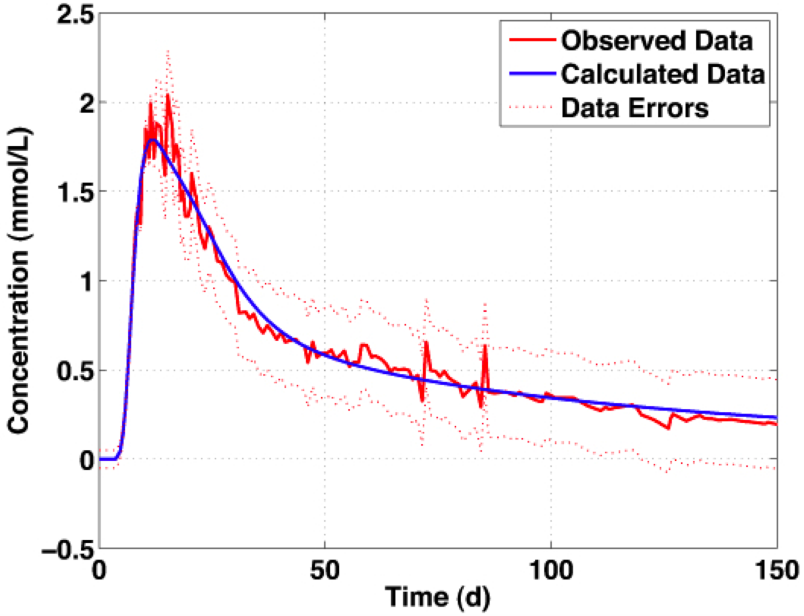

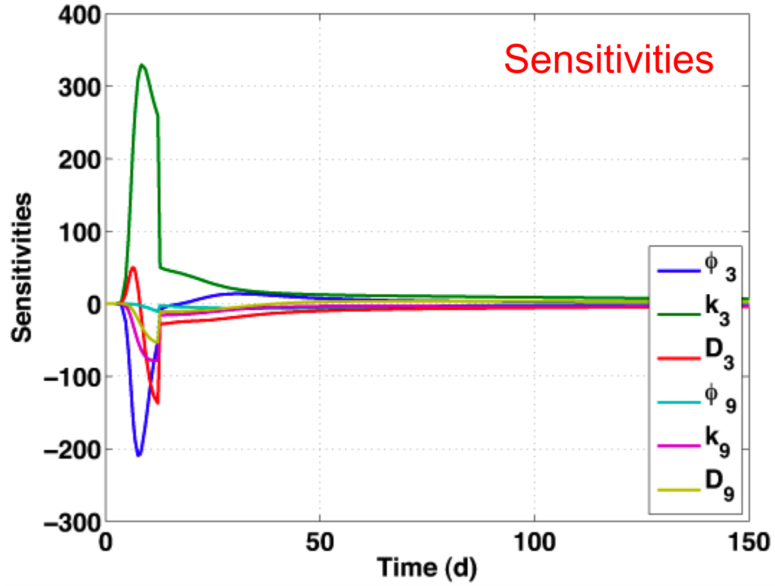

Zone	ϕ (-)	k (10^{-15} m^2)	α_D (m)
3 (fault)	0.0015	35.1	68
9 (host rock)	0.0069	0.0316	4.4

Rath & Kosack

Nearly perfect fit with very simple model geometry!

Soultz-sous-Forêts – Stochastic Monte Carlo Method

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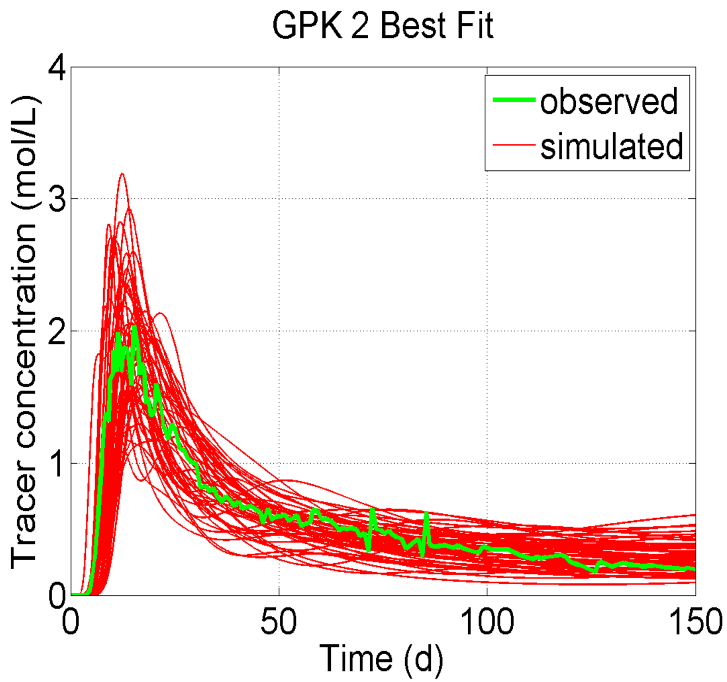
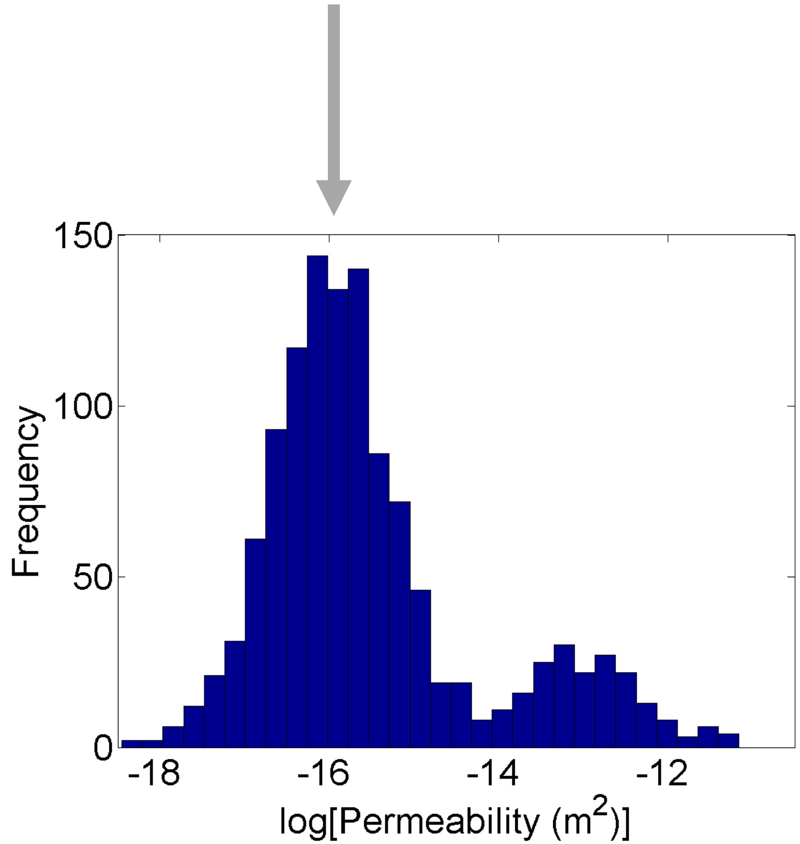
- Permeabilities picked from a bi-modal histogram



100 best fits of 5000 realizations



Soultz-sous-Forêts – Stochastic Monte Carlo Method

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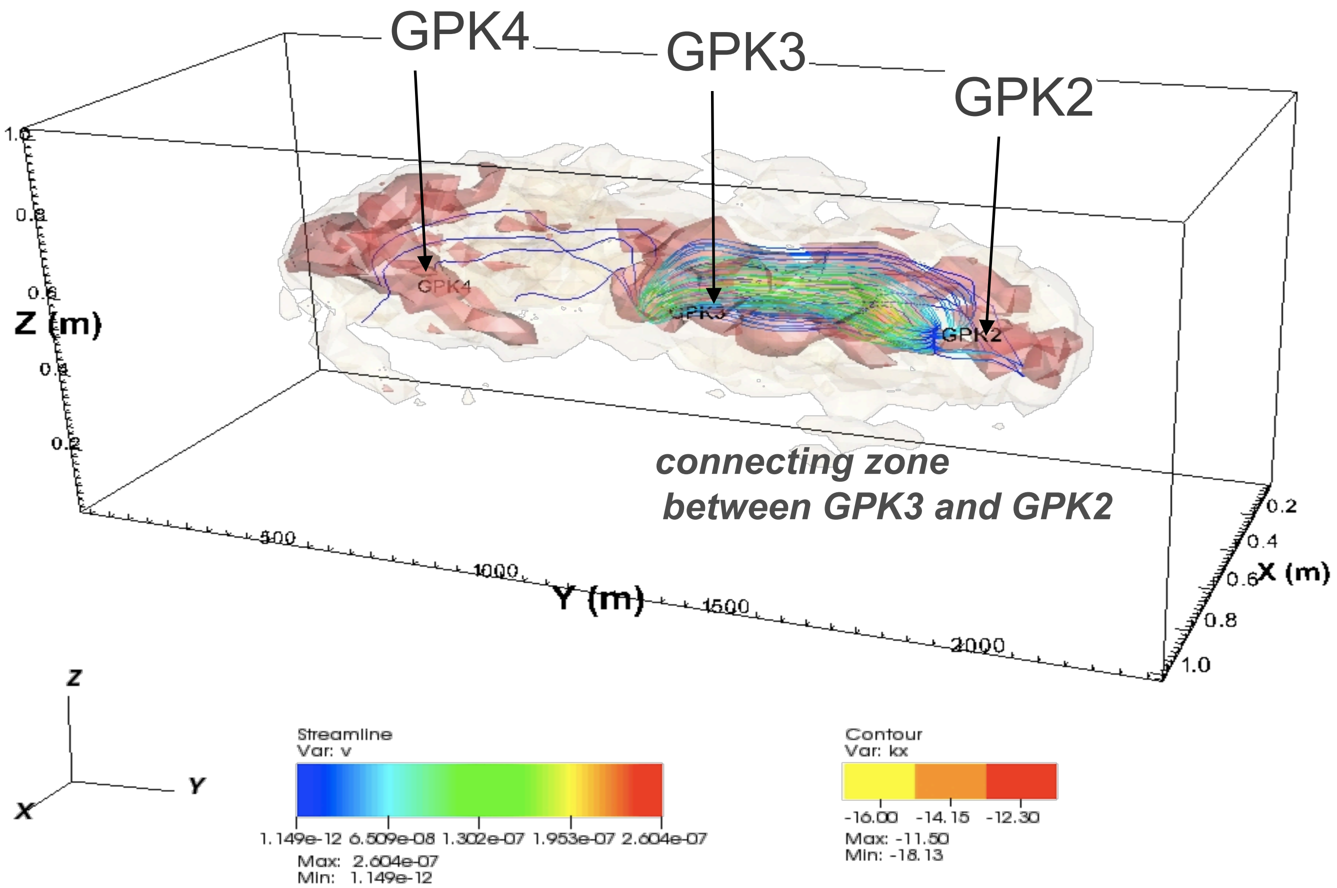
- Permeability distribution of best fit



Soultz-sous-Forêts – Stochastic Monte Carlo Method

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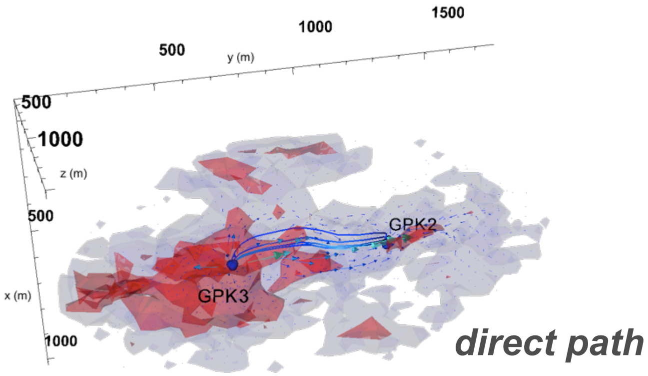
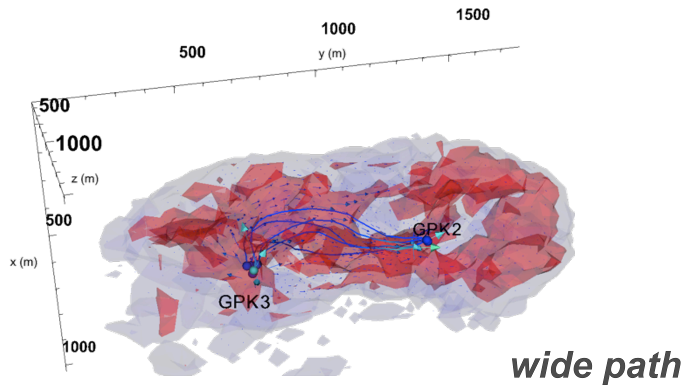
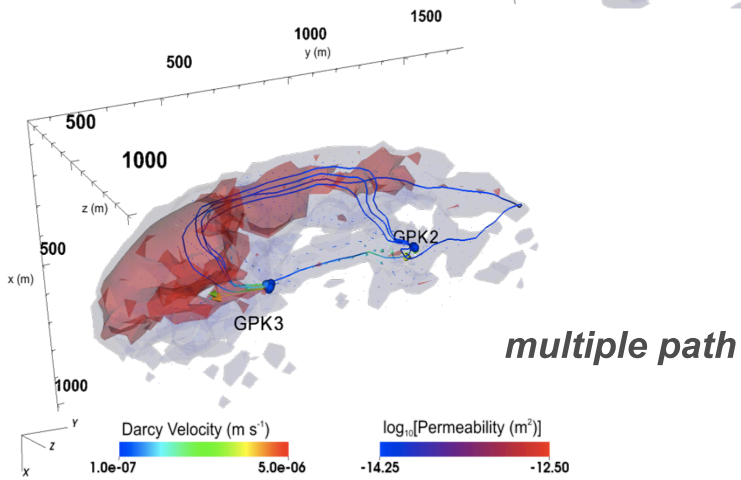
- Permeability and alternative flow paths

(Permeabilities sampled from bi-modal histogram)







Christian Vogt

Data Assimilation by Ensemble Kalman Filter (EnKF)

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- Idea underlying EnKF:
  whenever in time data becomes available with known errors, compare with data predicted by simulation and adjust system accordingly

- $$\Psi_k^f = F(\Psi_{k-1}^a) + \varepsilon_s$$ Forward propagation of the system Ψ
  $$d_k = H\Psi_k^f + \varepsilon_r$$ Data prediction

- $$\Psi_k^a = \Psi_k^f + \alpha K_k (d_k - H\Psi_k^f)$$ Adjust system according to a weighted difference between data and predictio

- $$K_k = C_{p,k}^f H^T \cdot (HC_{p,k}^f H^T + C_{d,k})^{-1}$$ Kalman Gain

k denotes time step; $C_{d,k}$ is data error covariance and $C^f_{p,k}$ is system error covariance obtained from an ensemble of system realizations which converges during repeated data assimilation steps

Soultz-sous-Forêts – Ensemble Kalman Filter (EnKF)

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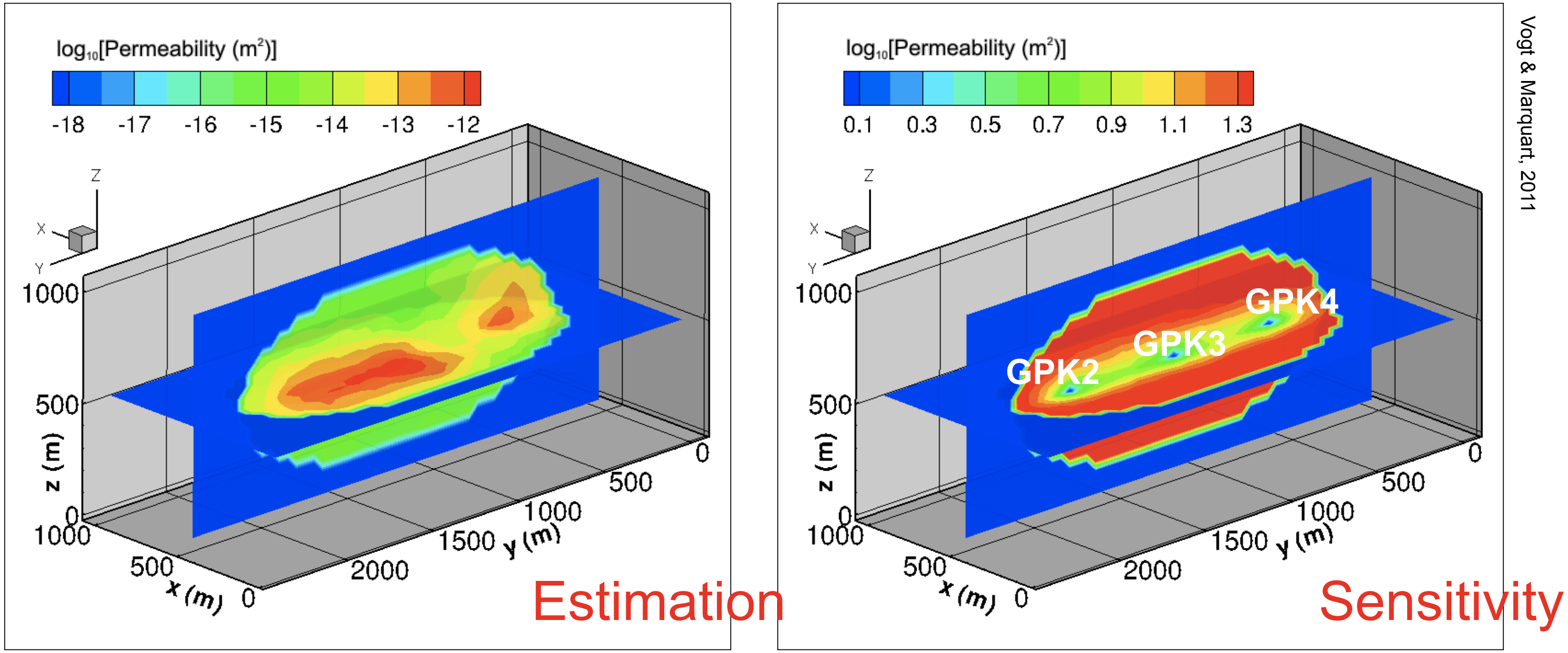

- 1 km × 2.4 km × 1 km (21 × 48 × 21 nodes); Injection at GPK3
- 2 production wells at GPK2 and GPK4
- Simulation time 150 days
- 2 iteration steps

Soultz-sous-Forêts – Ensemble Kalman Filter (EnKF)

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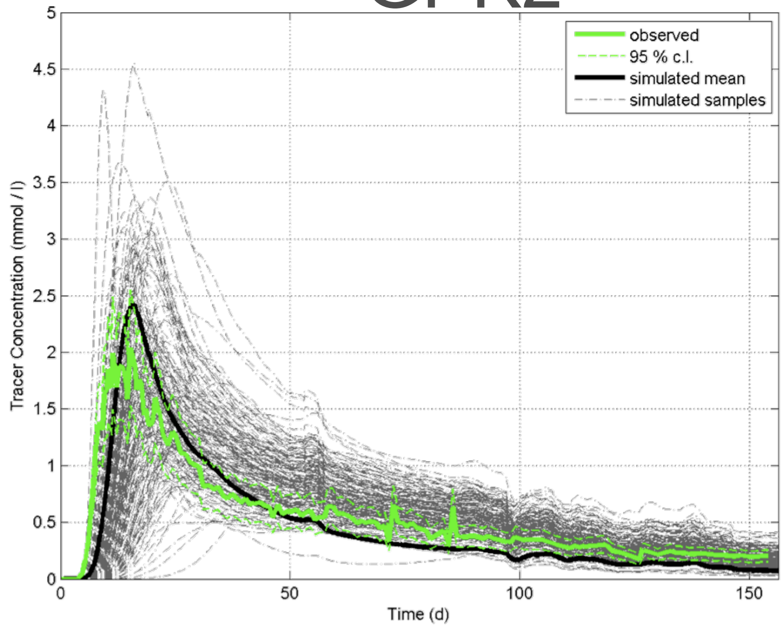
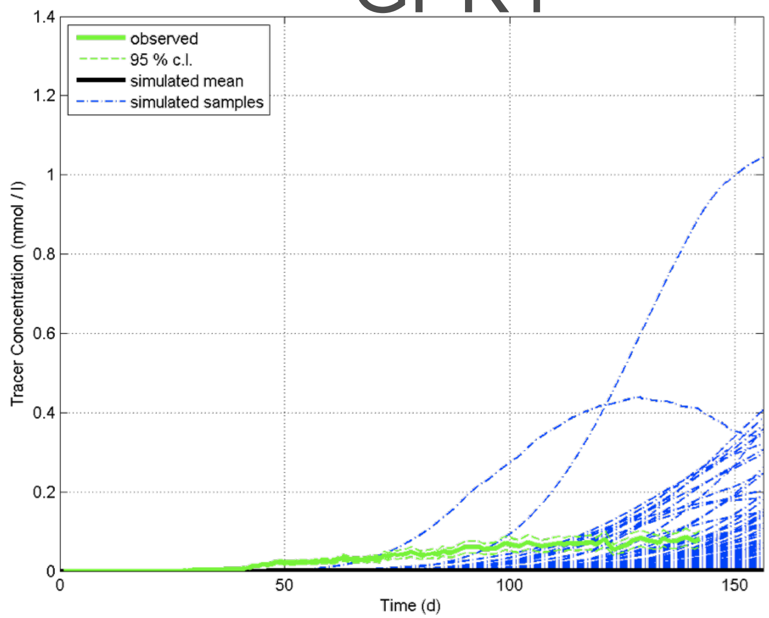
GPK2



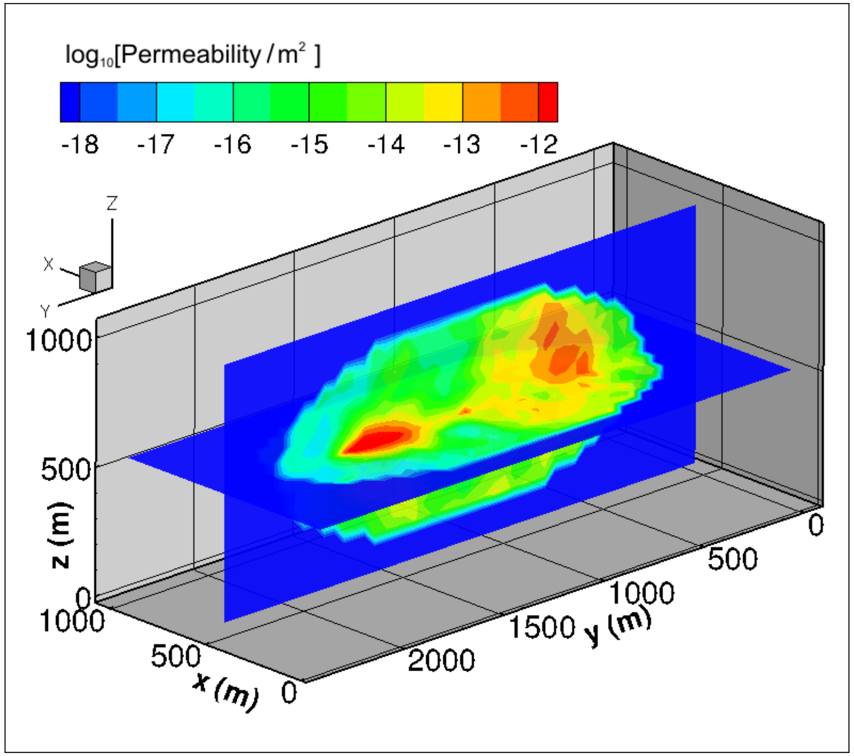
GPK4

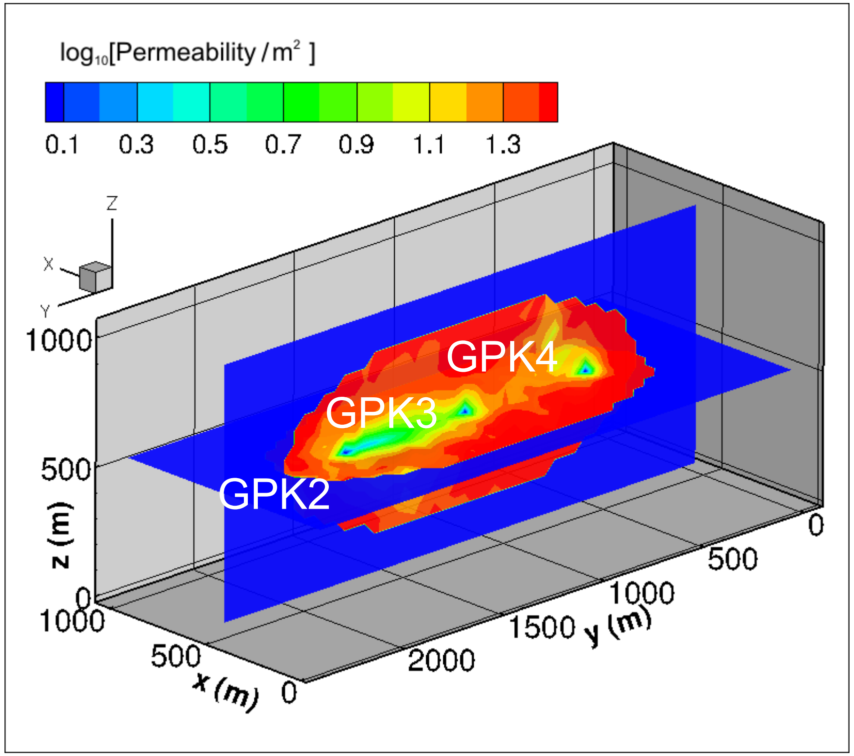


Most likely estimates comprising all data

RWTH AACHEN UNIVERSITY

Soultz – permeability ensemble mean and standard deviation





- 1 km × 2.4 km × 1 km (21 × 48 × 21 nodes); Injection at GPK3
- 2 production wells at GPK2 and GPK4
- 150 days simulation time
- 3 iteration steps
- 880 realizations

Soultz - porosity ensemble mean and standard deviation

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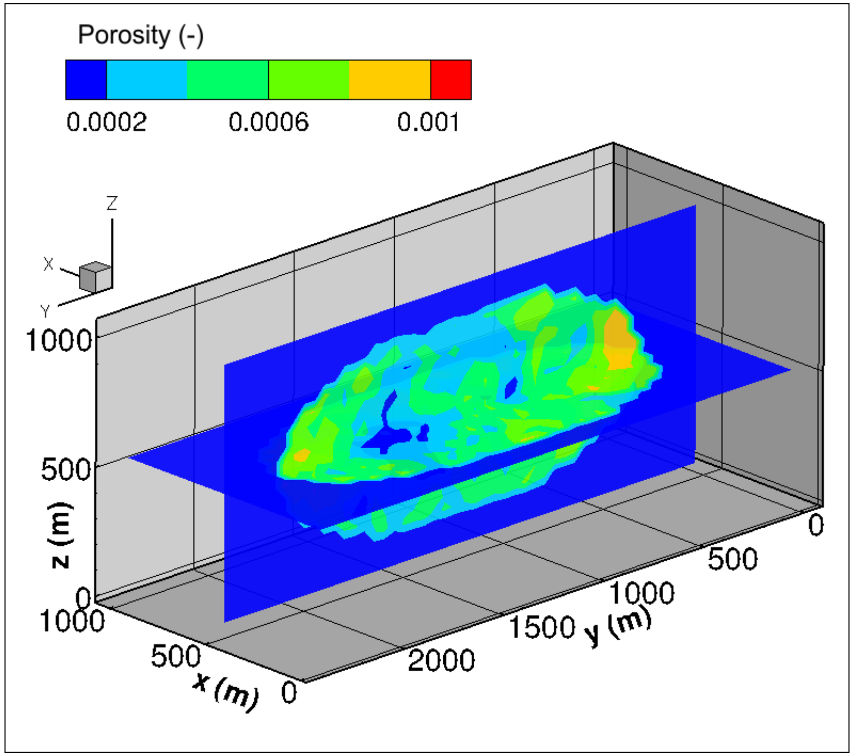

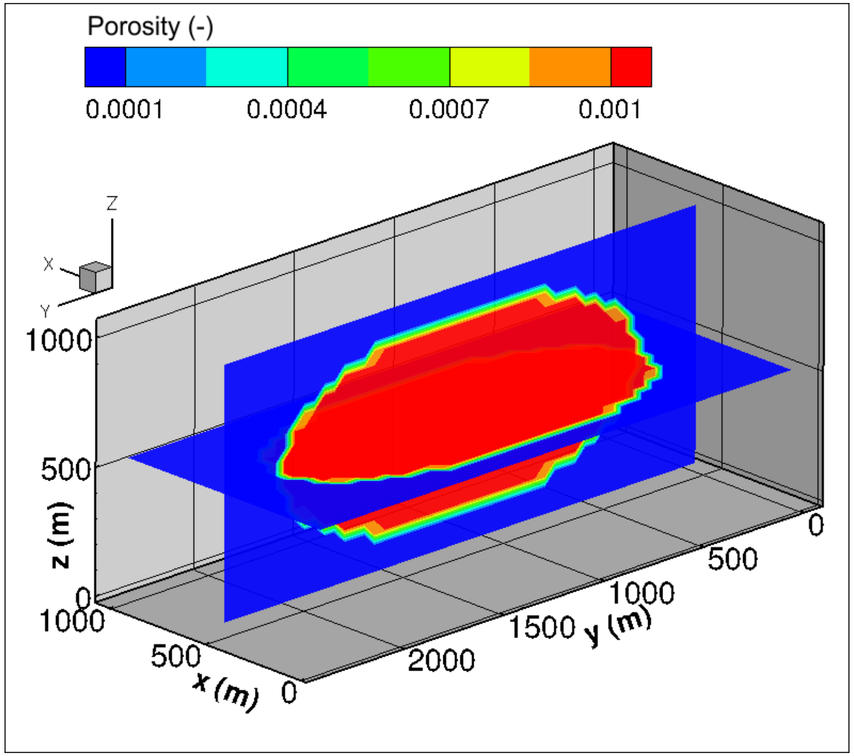

Test Location-Type 2: Sedimentary Basin

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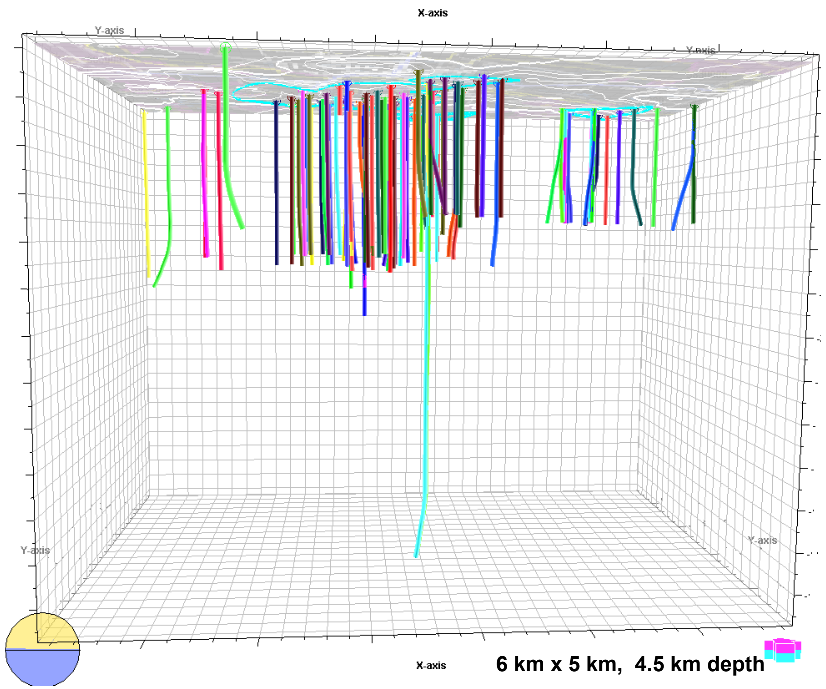
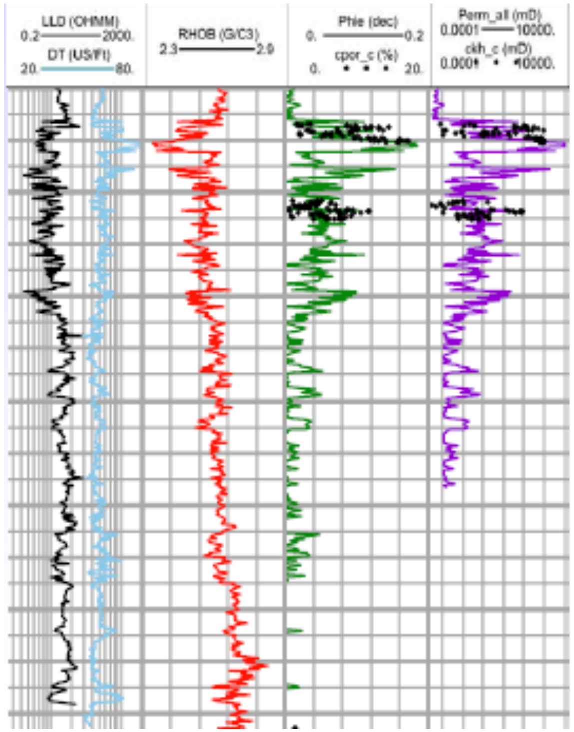
- **Northern German Sedimentary Basin**
  - sedimentary hydrocarbon reservoir
  - Data (provided by RWE Dea, Hamburg)
    - 3-D seismics
    - records and logs from ~ 100 boreholes
    - drill cuttings, cores from selected reservoir sections



6 km x 5 km, 4.5 km depth



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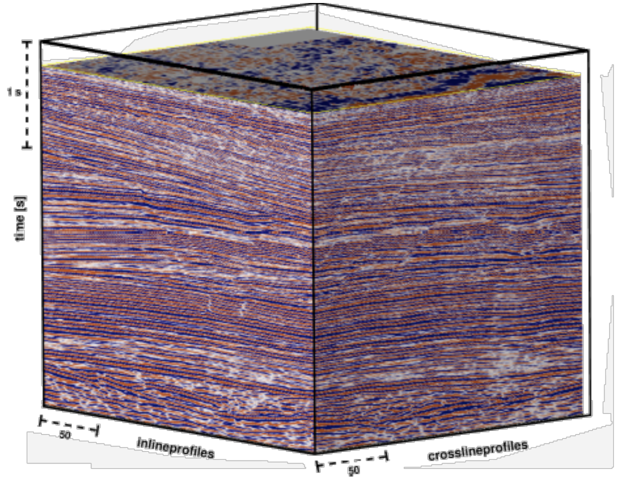
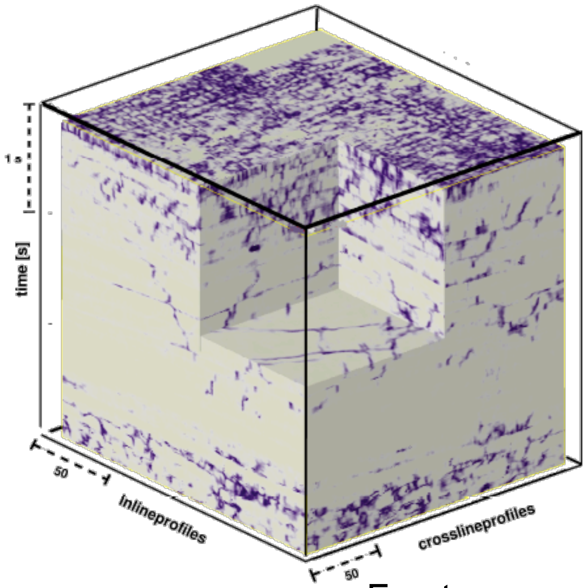
Sedimentary Basin – Reservoir Structure and Geometry

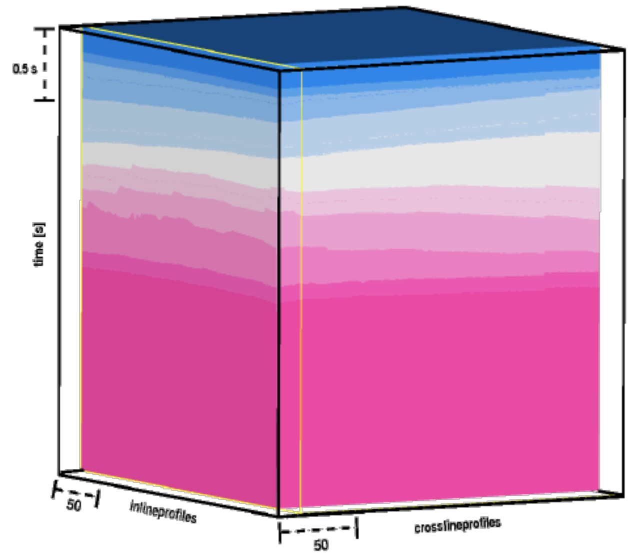
Kiel University
Development & application of new filter techniques for identifying structures



Seismic data



Fractures



Model

Katja Iwanowski-Strahser

Sedimentary Basin – Relation Between Rock Properties and v_P

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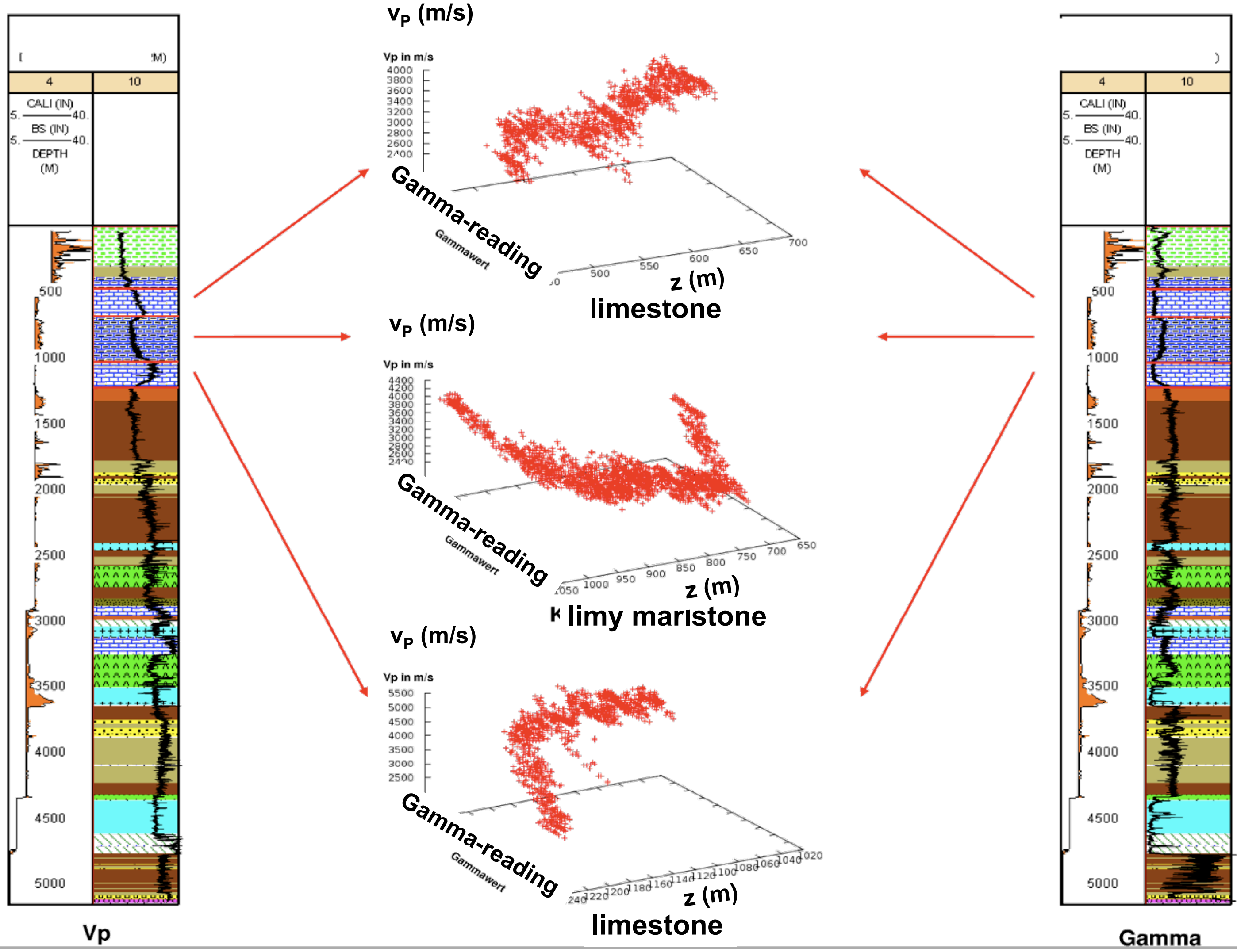
- for various rock types

Kiel University & Geophysica GmbH



Katja Iwanowski-Strahser

Model Generation: Sedimentary Basin

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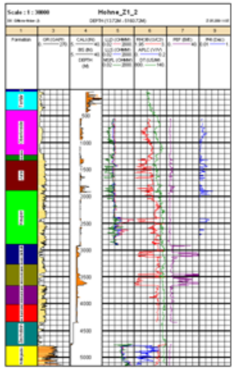
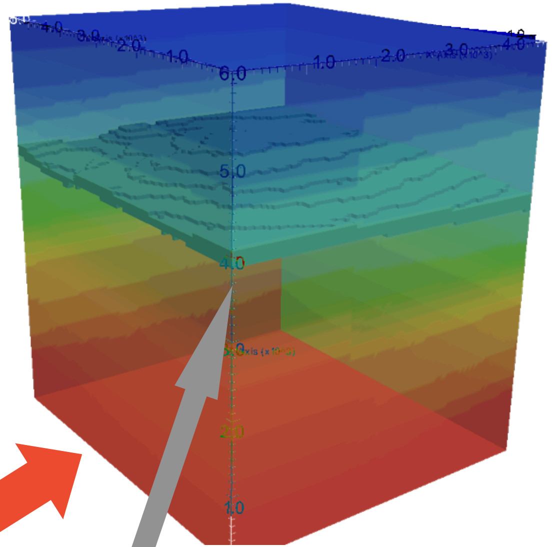


Logs

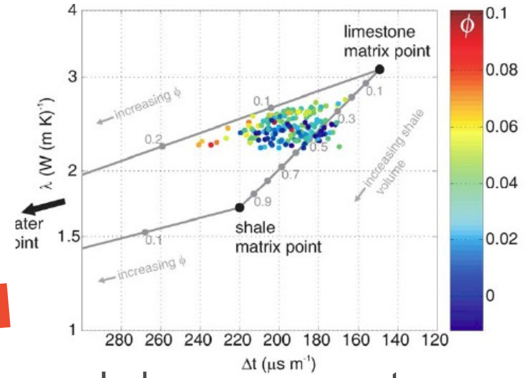
Numerical reservoir model
100 × 113 × 121 nodes



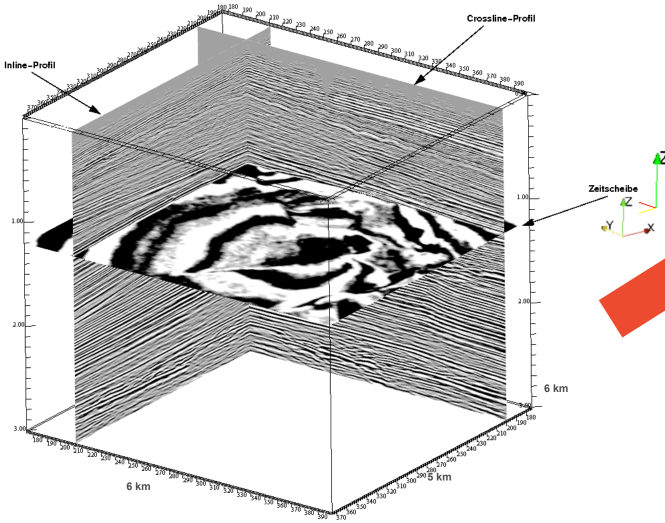
Site model

Target layer

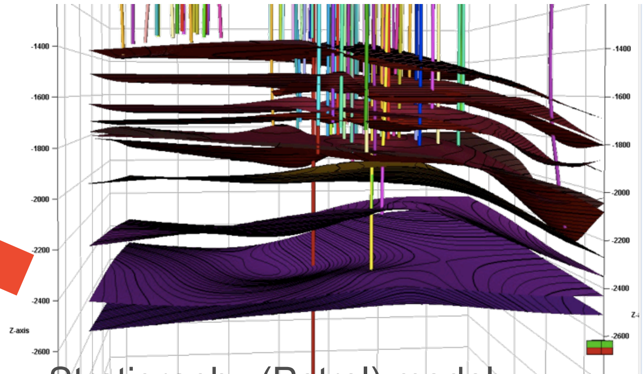
MeProRisk Group
Integration of geological, structural and rock property data in a 3-D model of the site



Lab measurements



Seismic processing



Stratigraphy (Petrel) model

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Thermal model

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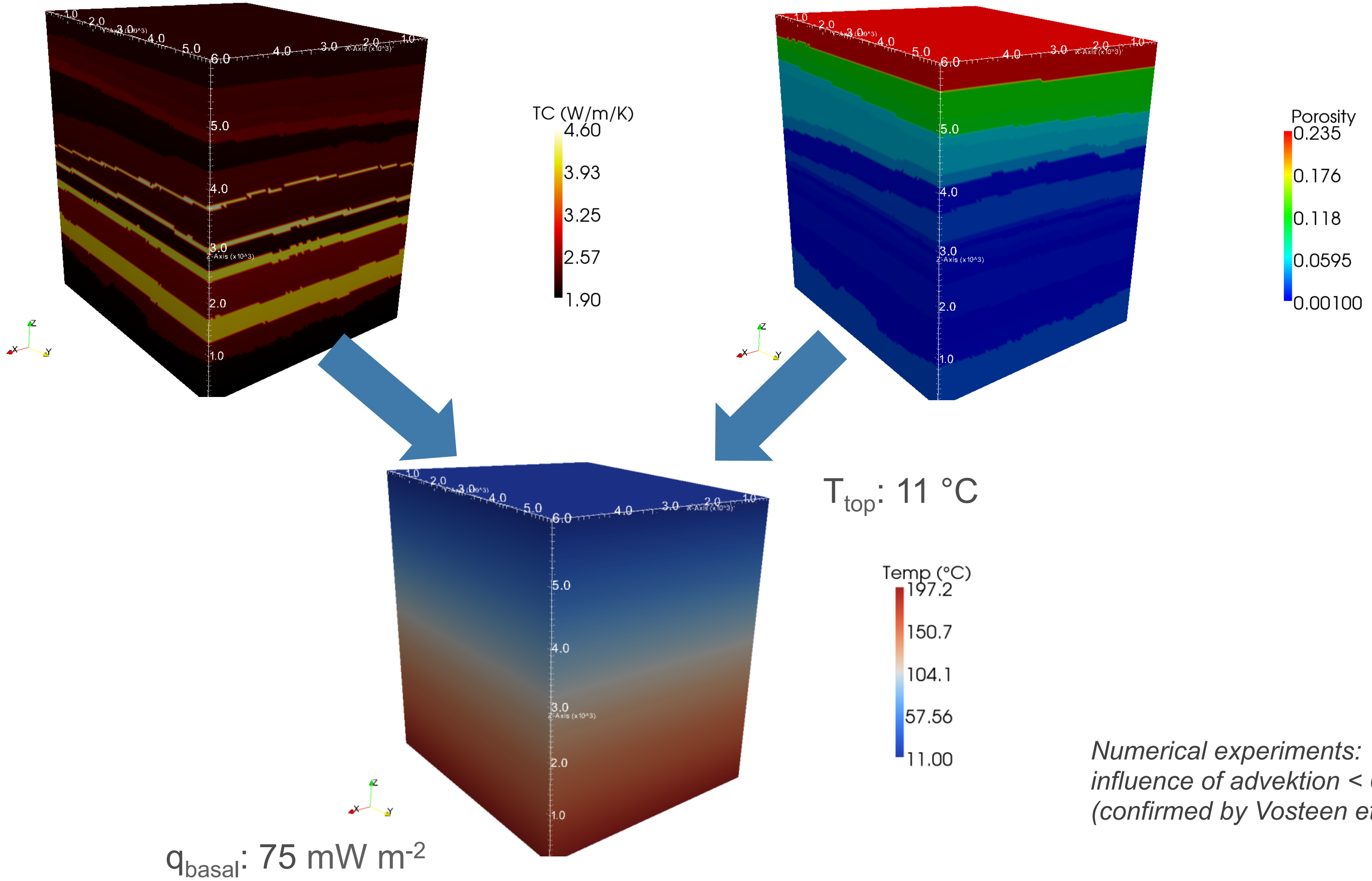
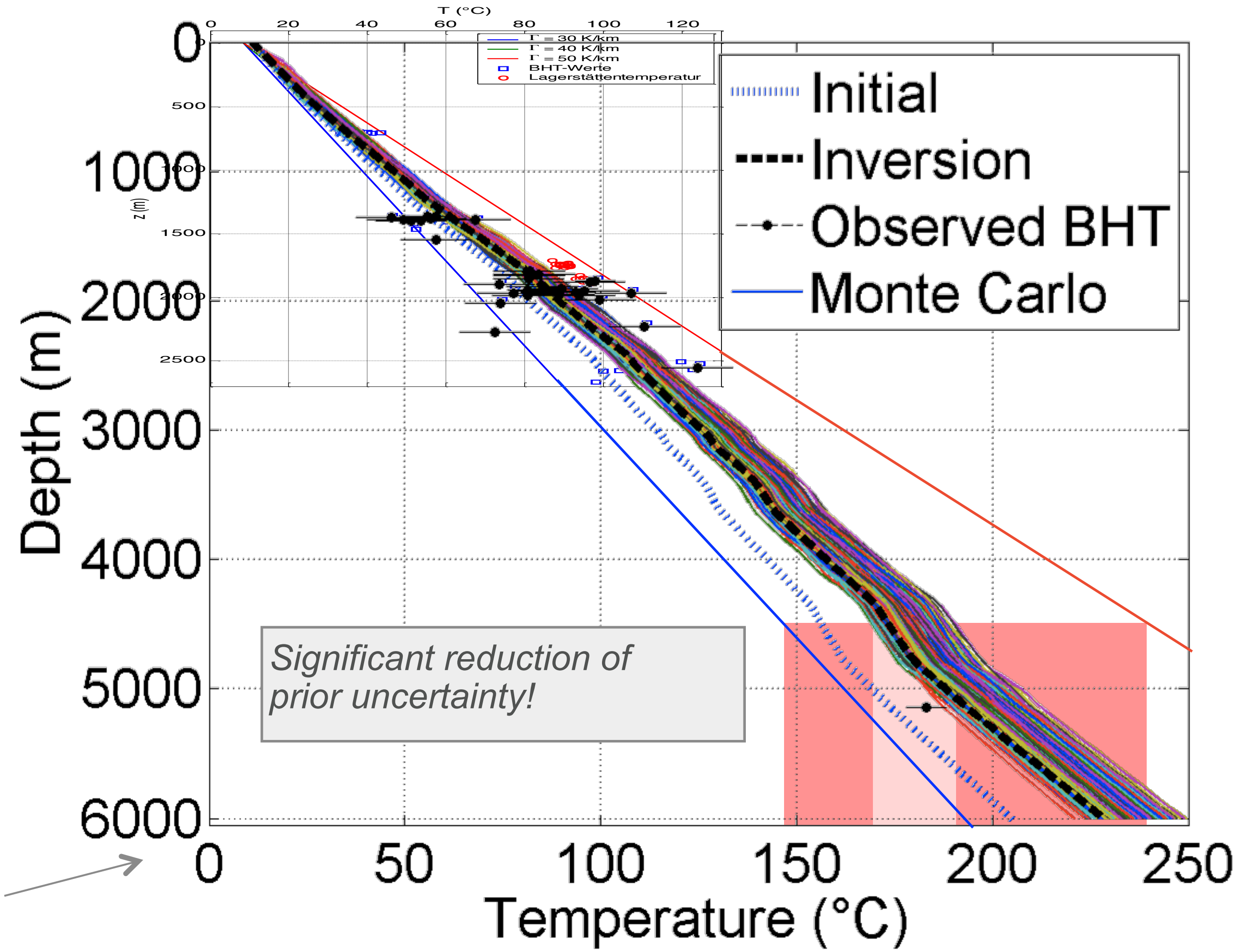


Numerical experiments:
influence of advektion < 0.25 K
(confirmed by Vosteen et al. 2004)

Predicted target temperature

Bayesian inversion of temperature based on BHT and simulations of 700 geostatistical Monte Carlo realizations

variable:
thermal conductivity,
porosity,
basal specific heat flow



Specific heat flow at 6000 m:
prior: 75.0 ± 10.0 mW m^{-2}
posterior: 77.7 ± 1.2 mW m^{-2}

Interactive Visualization

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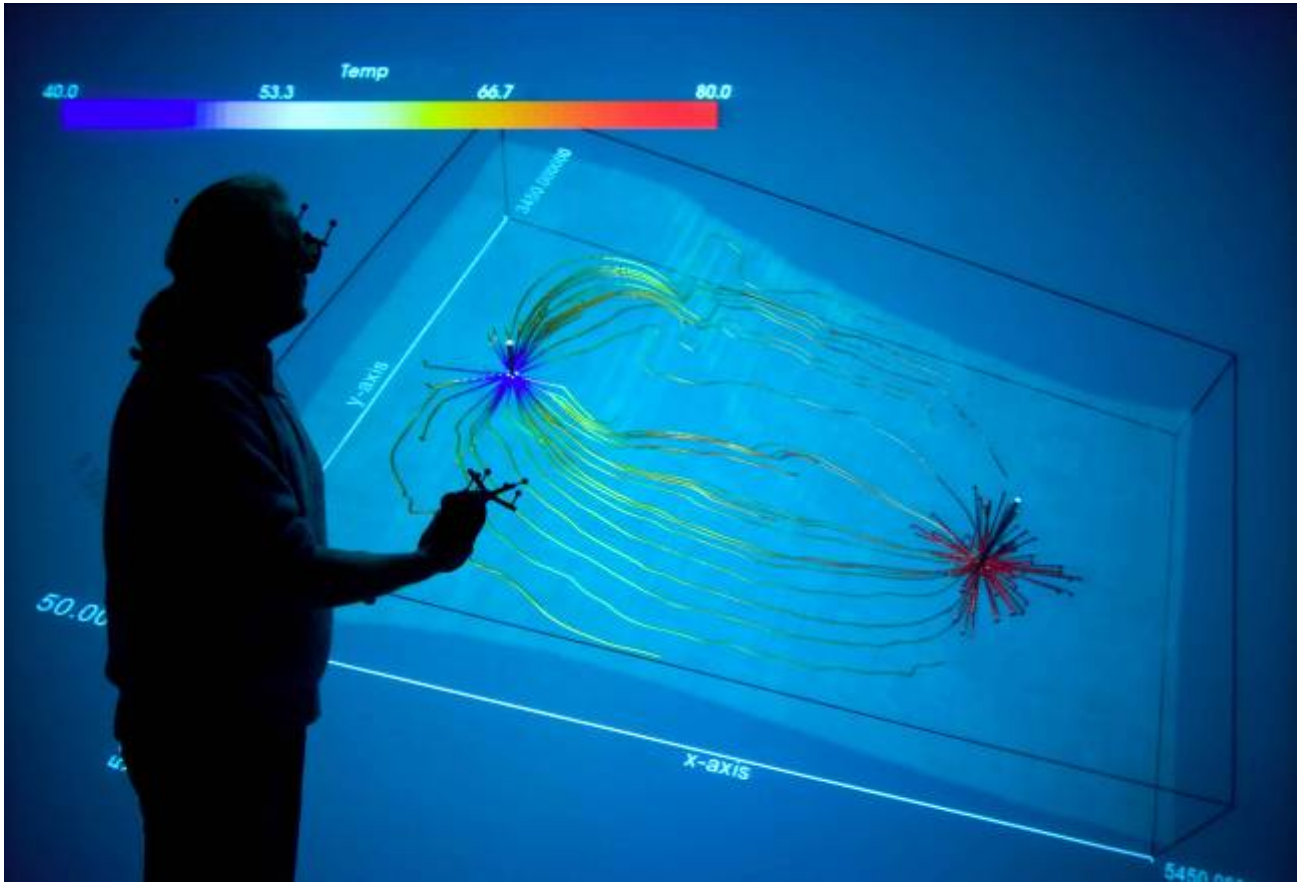
- Simulated streamlines of a geothermal doublet installation visualized in a virtual 3-D “cave” environment



Test Location-Type 2: Sedimentary Basin

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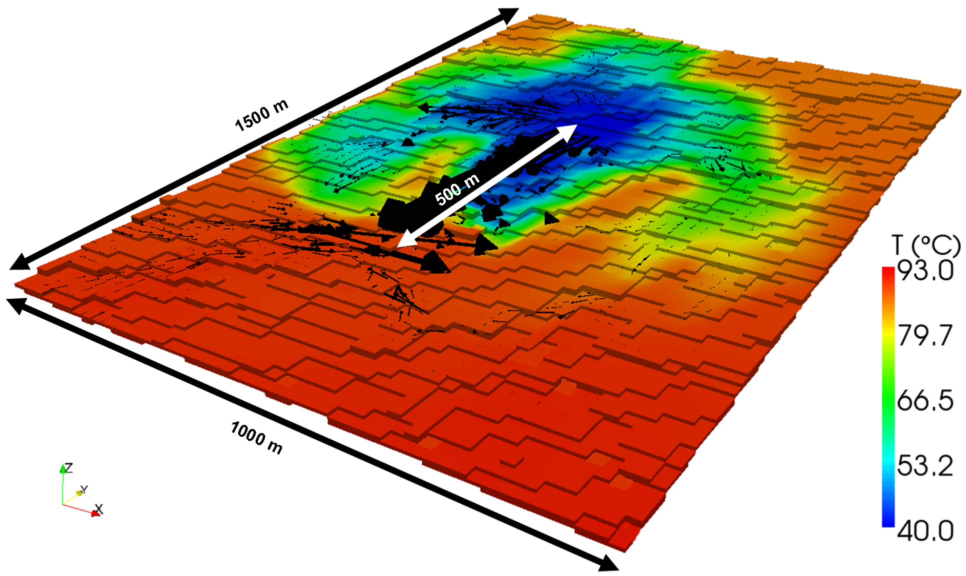
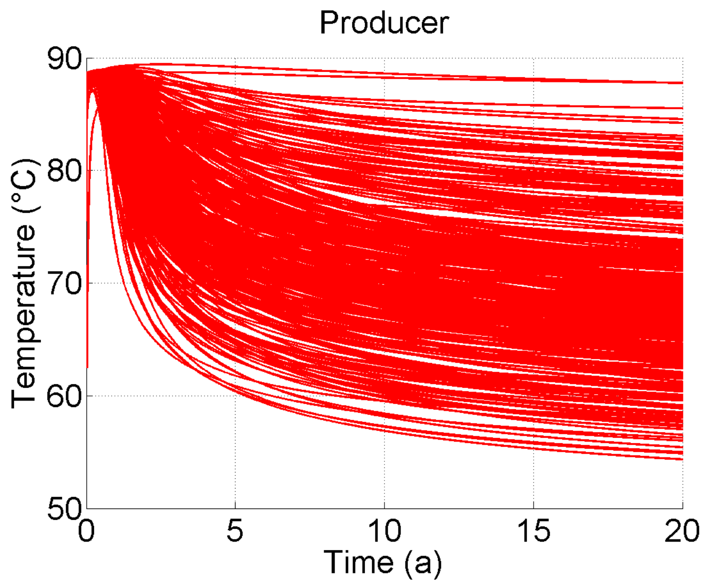
- Model of a geothermal doublet



- Sample realization

EnKF simulations



400 realizations

Limits on temperature and pressure

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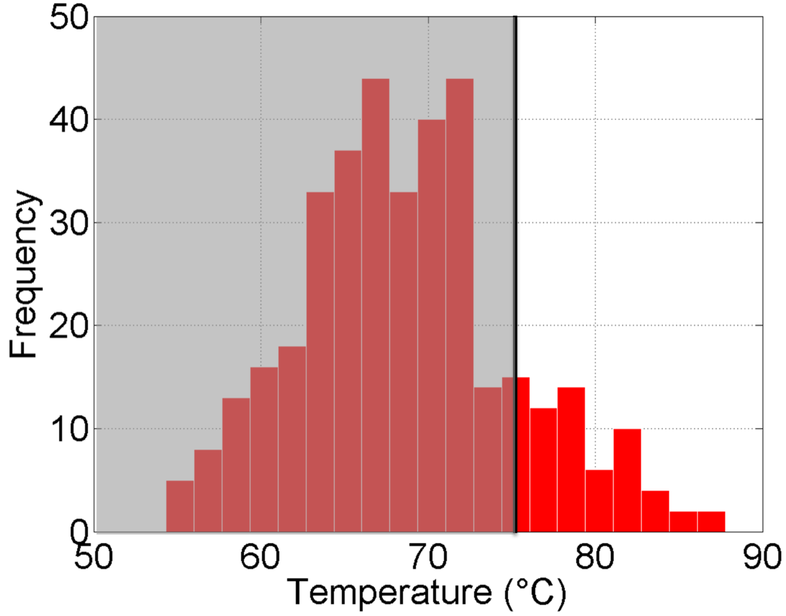
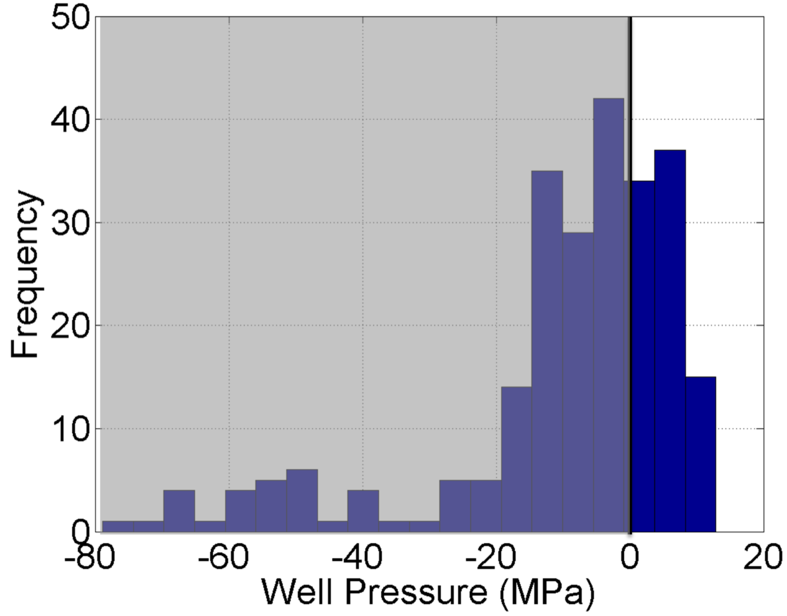
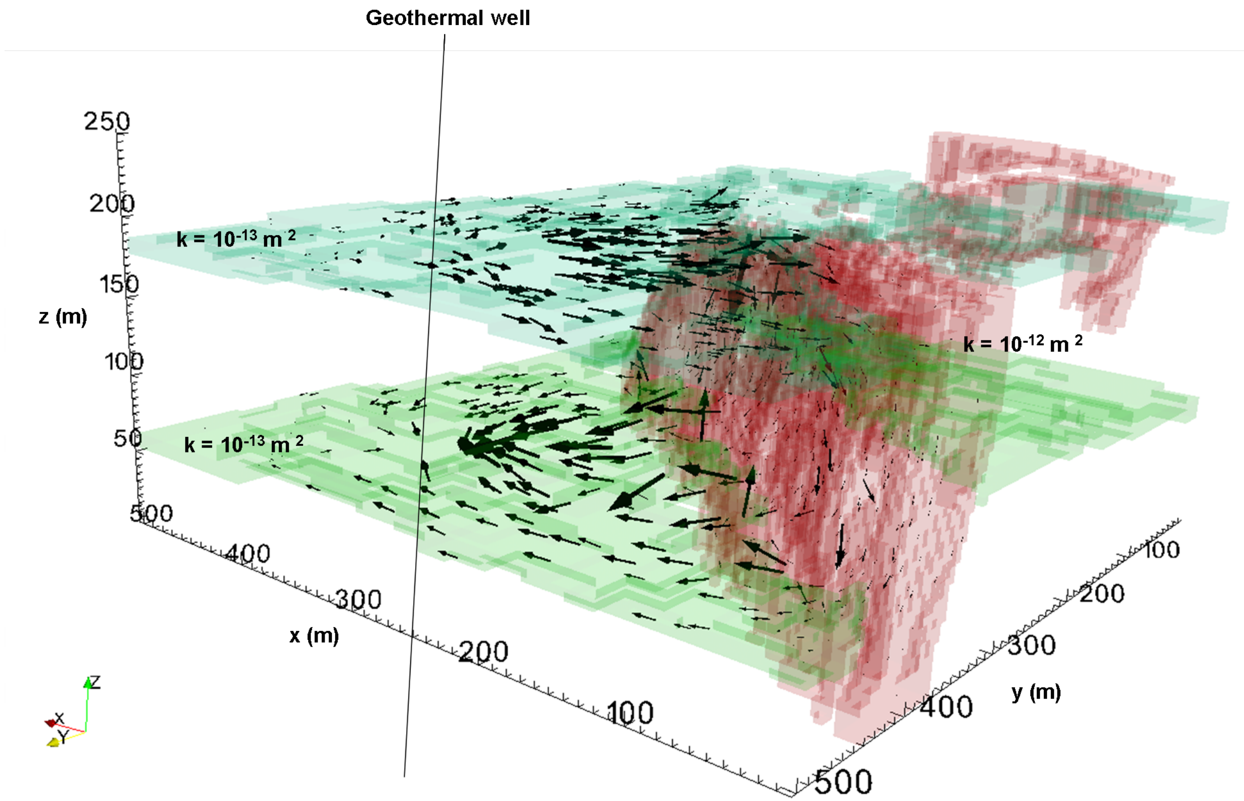




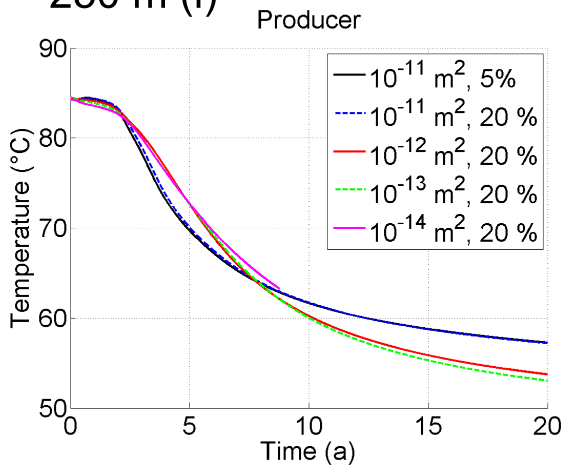
- Success probability for realizing 42 L/s at 75 °C: 1.6 %

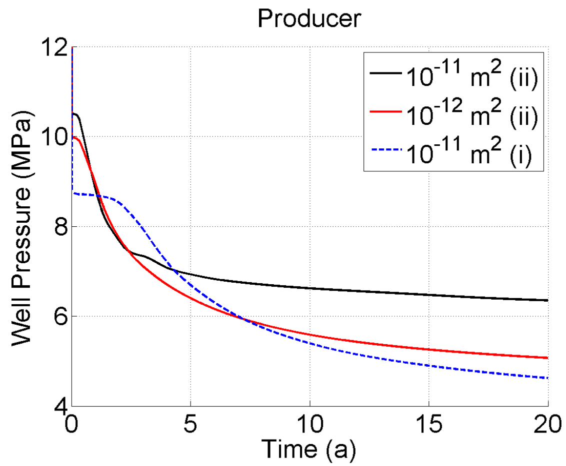
Single-well concept



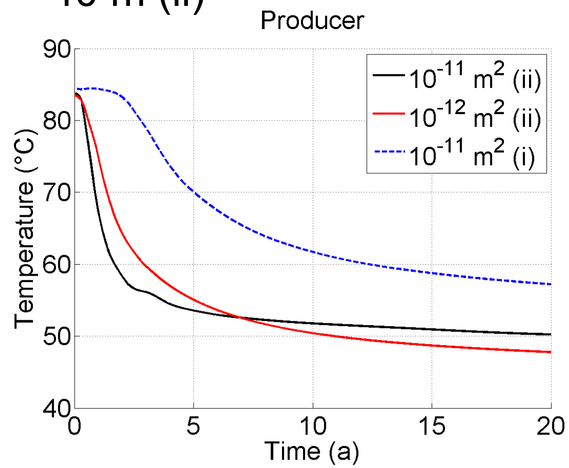
Single-well concept

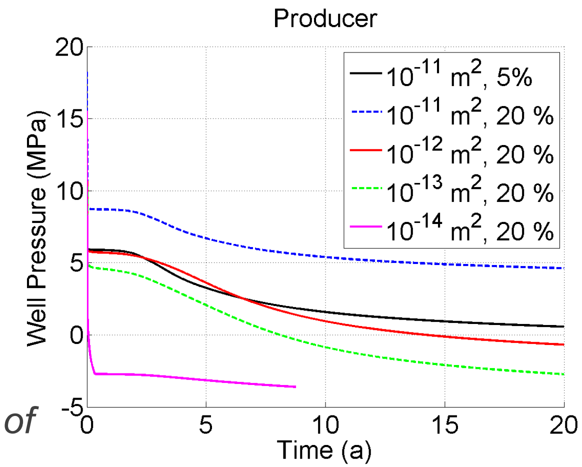
Distance well-fault: ~250 m (i)





Distance well-fault: ~40 m (ii)





Negative pressure: flow rate of 42 l/s cannot be established

Optimal experimental design (OED)

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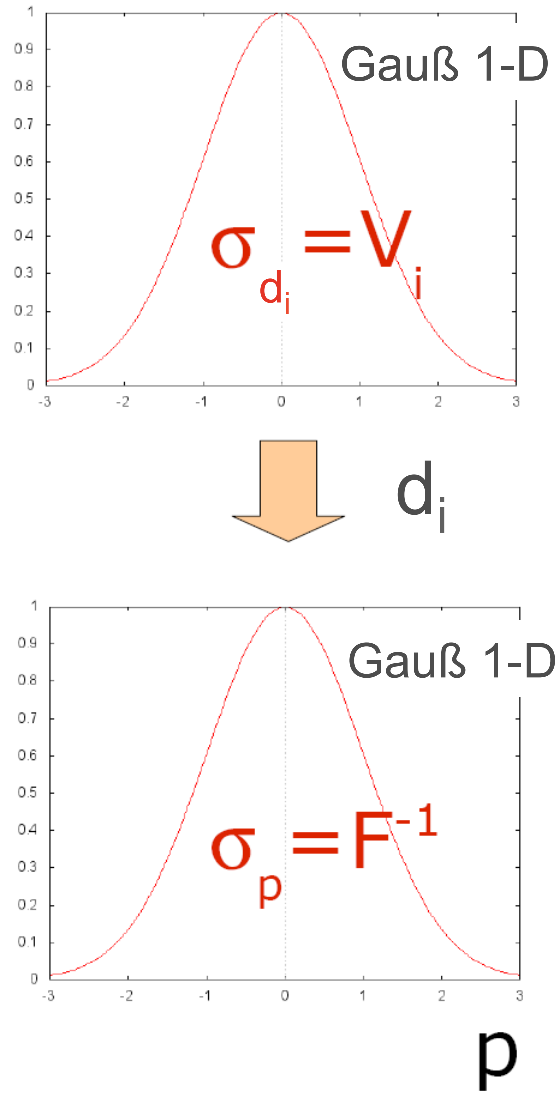
- Inversion - Parameter estimation
  - Find the optimal parameter vector **p*,** so that the simulation **g(p,x)** reproduces the observation **d** to best fit.

$$\Theta \sim \left(d - g(x,p)\right)^T C^{-1} \left(d - g(x,p)\right) \overset{!}{=} \text{Min}$$

- accuracy of estimated parameter
  - If N $\rightarrow \infty$ for noisy data: $\varepsilon(d_i, V_{di})$

    for estimated parameter: $\varepsilon(p^*, F^{-1})$
  - Fischer-Matrix: $F \sim \left(\frac{\partial g(x,p)}{\partial p}\right)^T V^{-1} \left(\frac{\partial g(x,p)}{\partial p}\right)$
- OED: Optimal experimental design:
  - Find the optimal experimental condition (position vector) **x*,** so that the parameter **p** is estimated to best precision based on the available data **d(x*)**



Optimal experimental design – Synthetic Model

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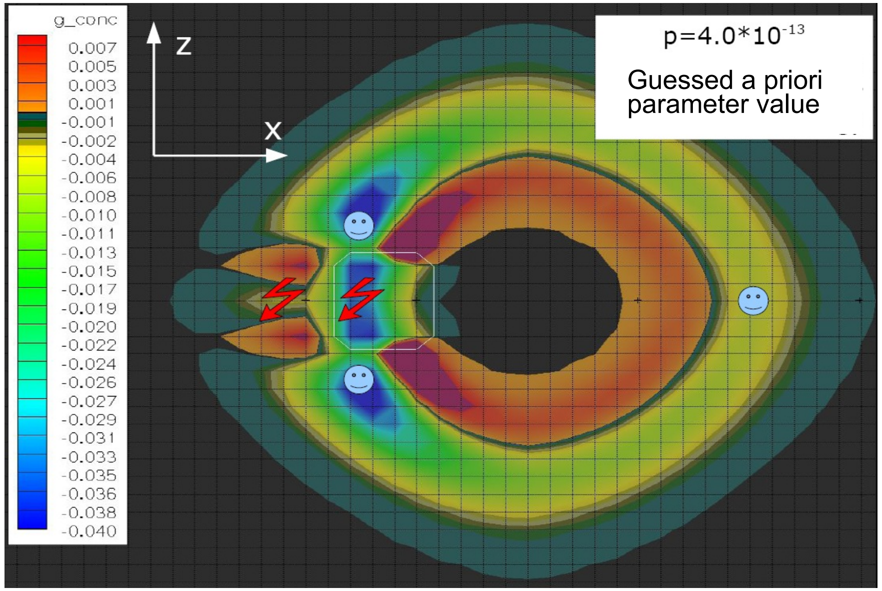
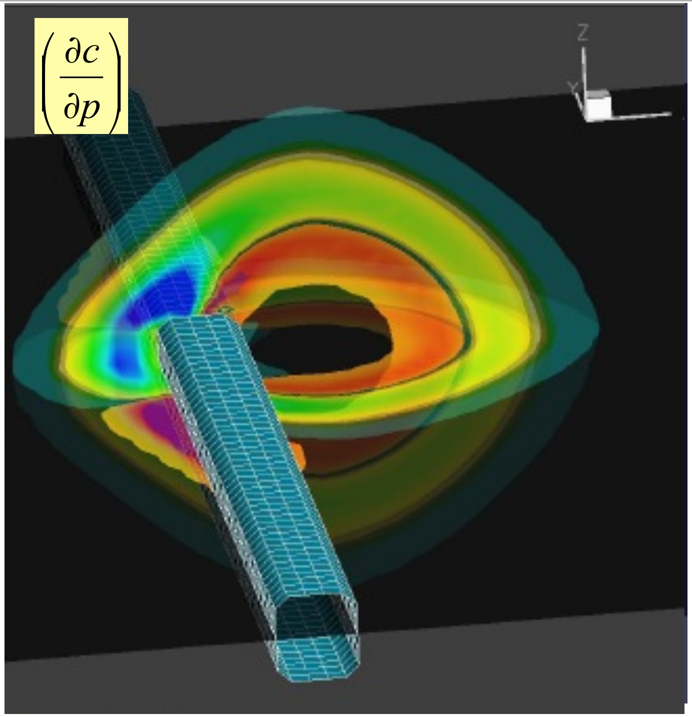
- Synthetic test case:
  - Best position to estimate the permeability of a fluvial sediment deposit based on a chemical tracer experiment
  - Best observation point: $\max\left(\partial c/\partial p\right)$





☺ : suitable observation site

⚡ : unsuitable observation sites due to large sensitivity to errors in parameter

Main MeProRisk achievements

E.ON Energy Research Center

- Improved seismic processing for identifying geological units, fractures, and faults
- New methods relating seismic observations to hydraulic properties
- Improved assessment of thermal and petrophysical rock properties by integrated interpretation of logs, core, and cuttings
- Improved numerical methods for reservoir simulation, parameter estimation, and quantification of uncertainty
- Innovative use of immersive visualization for appraisal of results
- Development of new methods for optimized siting of boreholes and field exploration (OED)

Thank you for your attention!