MeProRisk-II - A joint research project for optimization strategies and risk analysis for deep geothermal reservoirs

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ABSTRACT

The MeProRisk II project is a joint venture of 5 universities and a geophysical consultancy for defining and developing methods and workflows or evaluating geothermal reservoirs. These workflows combine information on the structure and the lithology of a reservoir with stochastic numerical simulation, estimation of uncertainty, and analysis of the probability of a successful geothermal reservoir use. Based on seismic and complementary surface observations, a first structural model of the reservoir is developed. Various filter methods applied to the seismic data allow identifying fractures and fissure networks. Petrophysical information is obtained from logging and lab studies on rock samples and attributed to the reservoir structural units in a stochastic framework. Numerical simulations of the reservoir accounting for the uncertainty of the petrophysical and structural parameters and an analysis of the Jacobian of the dynamic system are used to determine the uncertainty range for temperature and well pressure. With respect to the flow rates required for geothermal installations, this information is used for optimizing their lay-outs and estimating the associated risk of failure. This workflow is complemented by studies of micro-seismicity and stereographic 3D image analysis. The successful application of this approach is demonstrated for both sedimentary and crystalline reservoirs.

1. INTRODUCTION

Exploring geothermal fields and installing injection and production boreholes for exploiting geothermal energy for electrical power is expensive while at the same time there is no guarantee that these investments pay off. This risk turns out to be the major obstacle for a wider commercial use of geothermal energy. Increasing the invest or interest in geothermal ventures requires a reliable quantitative assessment of the risk of failure. The risk of failure consists mainly of insufficient temperature and flow rates of the produced geothermal fluid. While higher temperatures might often be reached by drilling deeper, an insufficient flow rate poses a much more severe problem. Therefore, reliable estimates of these properties are basic requirements for the economic and technical planning and operation of a geothermal reservoir. This starts by quantifying the uncertainty of these estimates at an early stage of reservoir exploration and continues with updates and modifications as reservoir development progresses.

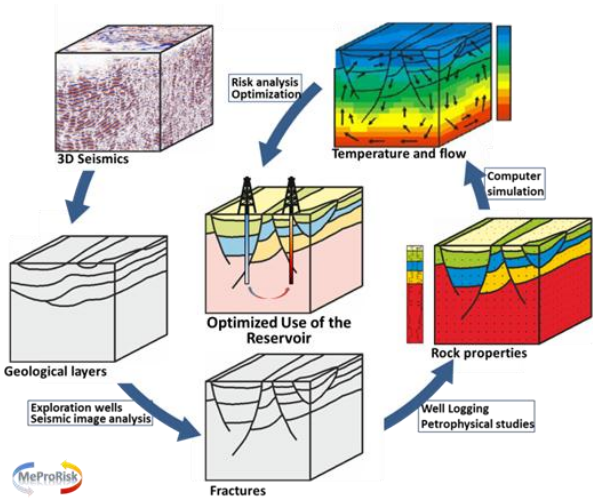


Figure 1: Sketch illustrating the workflow within the MeProRisk Research Consortium from interpretation of exploration data, over various stages of numerical simulation to an optimized geothermal installation.

Further, reliable quantitative estimates of the subsurface physical properties at an early exploration stage allow an optimized layout of the geothermal installation with respect to specific criteria ("optimal experimental design"). For instance, borehole location and depth may be determined under the constraint of maximizing the energy production for a given maximum drilling depth defined by a limited investment.

To this end, optimization criteria need to be specified mathematically and put in functional relation to the physical processes in the reservoir for defining and maximizing an objective function. The parameter

space for possible configurations is thus defined by both physical and economic boundary conditions.

2. WORK DISTRIBUTION WITHIN THE MEPRORISK RESEARCH CONSORTIUM

Over the past years, the MeProRisk Research Consortium has been developing and adapting basic theory and numerical methods. These methods allow determining the 3D reservoir structure and distribution of faults and fractures. Hydrothermal rock properties were assigned to rock units in a statistical sense and with reliable error estimates as input for numerical simulations and predictions of reservoir behaviour (see Fig. 1). Some of these results are presented here.

Calculations of this kind can be used on the one hand for a risk analysis of the reservoir and on the other hand as a base for an optimized reservoir layout with respect to given constraints (minimizing drilling cost, high heat production, quick return of investment, etc.). For a risk analysis, see Vogt et al. (2013, this issue).

The MeProRisk project requires combining expertise in various fields such as: (1) seismic interpretation and assessment of reservoir geometry, (2) interpretation of logging data for petrophysical properties and assignment of rock properties, (3) numerical programming and simulation of fluid, species, and heat flow, (4) inverse methods, error estimation and optimization analysis, and (5) virtual reality visualization techniques.

The structure of the cooperation among and expertise of the MeProRisk partners is reflected by the project structure (Fig. 2).

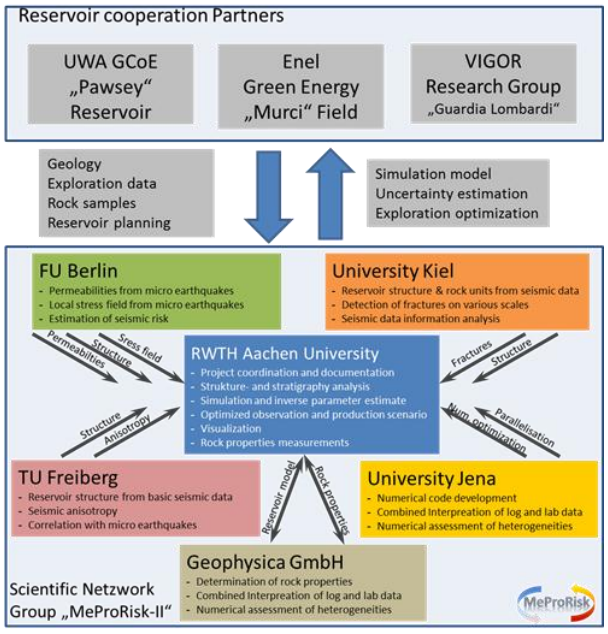


Figure 2: Structure of the cooperation, working fields, and expertise within the MeProRisk Research Consortium

3. METHODS OF MEPRORISK RESEARCH CONSORTIUM

Over the past four years various methods, numerical codes and cooperation strategies have been developed by the institutions shown in Fig. 2. Based on improved methods for identifying the subsurface structure and rock properties from seismic data, log interpretation, and laboratory measurements, numerical simulation software for double diffusive porous flow (SHEMAT-Suite, Rath et al. 2006) has been developed. This allows for improved estimates of temperature distributions and flow rates at depth by forward and inverse modeling.

3.1 Structure, fault and fracture detection in refection seismic data

A first step in reservoir assessment requires reliable information on the subsurface structure. This is obtained from conventional seismic interpretation (Fig. 3a) and lithological reconstruction derived from borehole information (Fig. 3b). Once the structure is defined, a gridded reservoir model is constructed (Fig. 3c) and a target layer or target rock unit is identified.

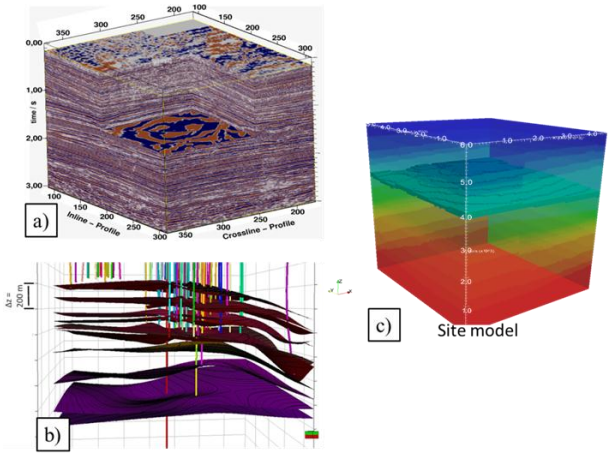


Figure 3: Assessment of the reservoir structure a) seismic model, b) lithological interfaces based on borehole information, c) reservoir model of the site with the target layer indicated. The site is a sedimentary reservoir in the Northern German Basin (Vogt et al. 2013).

In the process of structural model construction, the identification and spatial orientation of faults and fractures is essential. In particular for hydraulic and thermal simulations information on fault and fracture geometry is crucial for understanding the flow pattern. Here we demonstrate the process of fault and fracture identification using the reflection seismic data set ISO89 3-D (Stiller 1991; Körbe et al. 1997) of the German Continental Deep Drilling Program KTB (e. g. Emmermann and Wohlenberg 1989). The KTB drill hole is in crystalline bedrock and the geological structure is characterized by a few large sub-vertically dipping seismic reflectors and a network of smaller fractures.

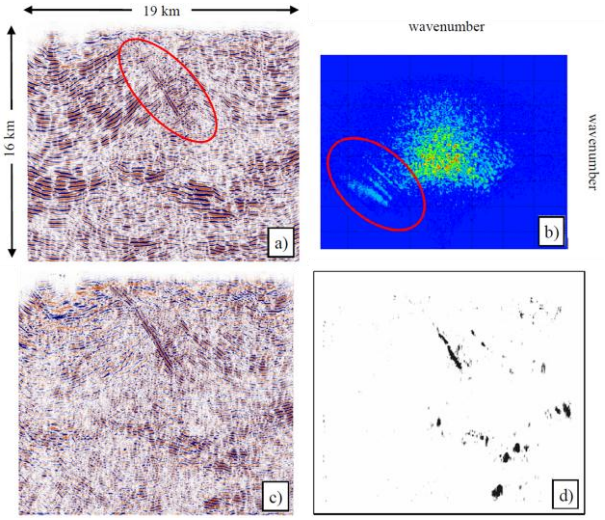


Figure 4: Identification of large scale faults by *k-k* filtering: a) original data in 2D space domain, b) *k-k* spectra in 2D wavenumber domain, c) *k-k* filtered data, d) envelopes of *k-k* filtered data in 2D space domain (Szalaiová 2012). Dataset is KTB ISO89 3-D (Stiller 1991; Körbe et al. 1997).

In this representation, individual features in 2D space domain, characterized by a unique dip, can be identified also in the 2D wavenumber (*k-k*) domain (Yilmaz 2001). The seismic 3D data cube is interpreted in terms of vertical cross-sections in 2D space domain. These data are transformed by a 2D Fourier transform to the 2D wavenumber domain. The Fourier transform is decomposing the input *z-x* data in such a way, that interesting dips can be identified in the wavenumber space, suppressed by muting and transformed back to the *x-z* domain for further processing or interpretation.

In Fig. 4 we demonstrate the *k-k* filtering applied to one slice of the KTB data cube. As seen in Fig. 4a, the majority of the features exhibit a sub-horizontal dip and plot in the center of the *k-k* spectra (Fig. 4b). The inclined, large-scale faults can be easily sorted out from the rest of the events (see red ellipses in Figs. 4a and 4b).

By filtering in the wavenumber domain interesting structures such as the large-scale fault can be enhanced when back-transformed into the 2D space domain (Fig. 4c). In this way the large scale faults can be isolated for a further interpretation (Fig. 4d). This method was applied successively to all cross sections of the KTB seismic dataset.

In contrast to first order reflectors (large faults), smaller fractures produce incoherencies of the seismic traces. To isolate these features a Garbor filter (Field 1987) can be applied which is basically a band-pass with an adjustable center frequency, orientation and bandwidth. If properly adjusted, it reacts strongly to specifically oriented structures and weakly to all others. This ability makes it suitable for fracture identification in seismic data sets (Admasu 2008). The application of the Garbor filter is demonstrated in Fig. 5.

In a second step, the results from the *k-k* filter and the Garbor filter are combined in the 3D cube and the probability of interconnected faults is calculated based on a fractal analysis following Turcotte (1997) (Fig. 5 d) and then attributed to unscaled permeabilities (Fig. 5e and 5f). These unscaled permeabilities are scaled to absolute values based on permeability ranges for the KTB rocks (Fig. 6b).

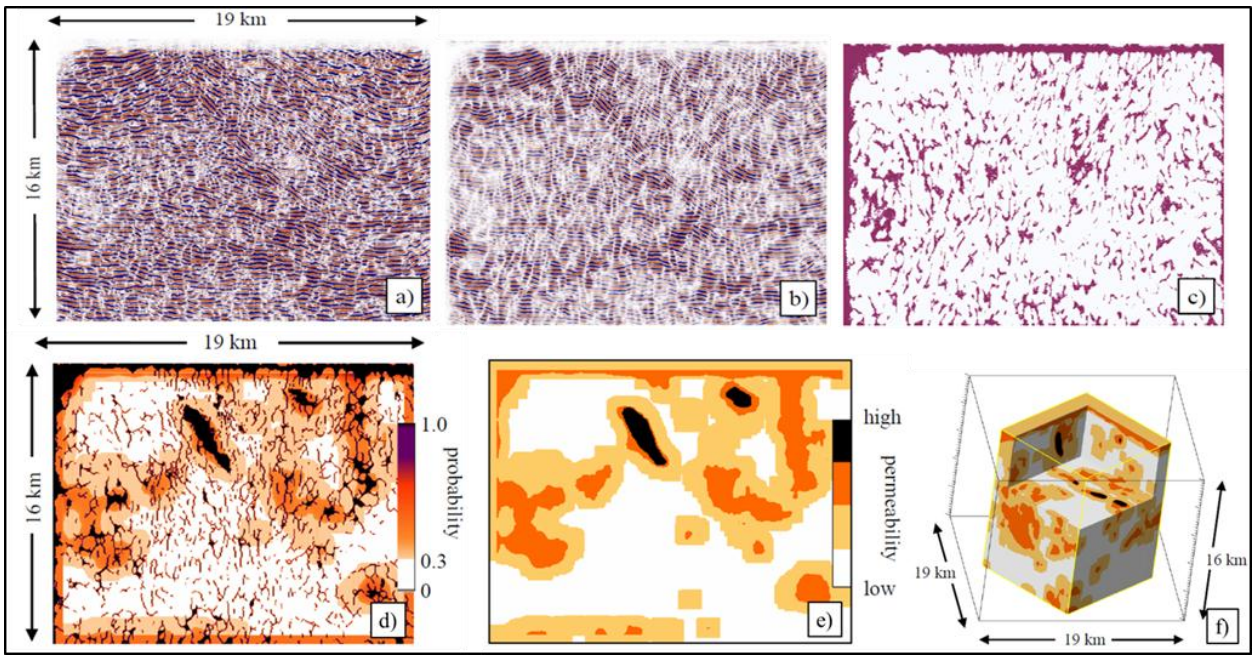


Figure 5: Application of the Garbor filter to one slice of the KTB seismic data and identification of permeability distribution: a) original data, b) Garbor filtered data, c) isolation of fractures, d) combination with large-scale faults and probability of connected faults or fractures in the 3D cube, e) derived unscaled permeabilities, and f) for the entire cube (Szalaiová 2012).

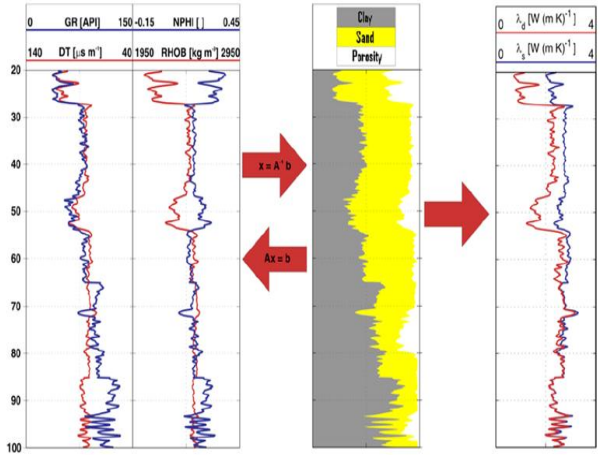


Figure 6: Calculating dry and saturated thermal conductivity (λ_d and λ_s) profiles from logs: left: observed log [gamma ray (GR), neutron porosity (NPHI), acoustic slowness (DT), bulk density (RHOB)]; center: inverted rock components and porosity; right: calculated dry and saturated thermal conductivity.

3.2 Determination of probability distributions for reservoir properties

Physical properties are attributed to reservoir rocks by combining information from logging, measurements on core samples and literature values. Log data is inverted for rock composition and porosity. Based on these properties and assuming a geometric mixing law for various minerals (Clauser 2011), dry and saturated thermal conductivities are calculated (Fig. 6). Porosity and thermal conductivity are binned in appropriate ranges and combined with data obtained by direct measurements on cores resulting in histograms for the main reservoir properties (Fig. 7).

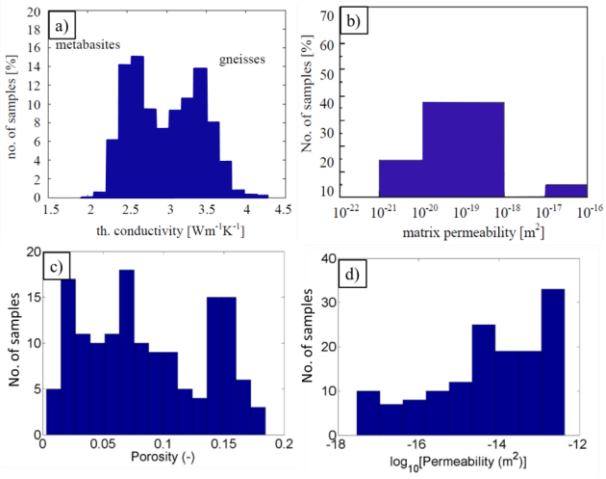


Figure 7: Histograms of reservoir properties, a) and b) thermal conductivity and permeability for KTB rocks (Szalaiová 2012), c) and d) porosity and permeability for a reservoir in the Northern German Basin (Vogt et al. 2013).

Histograms of this kind are constructed for each reservoir property. However, particularly permeability histograms need to be constructed carefully taking into account the up-scaling from core samples over log data to reservoir scale. Large faults are incorporated in reservoir models explicitly.

3.3 Reservoir simulation, inversion and stochastic modelling

Once the geometry and the rock properties of a reservoir are assessed, a numerical simulation of the hydrothermal processes in the reservoir can be carried out. This might be natural convection or forced fluid circulation assuming an injection-production installation. Our simulations are based on the in-house simulation software SHEMAT-Suite (Rath et al. 2006) which solves the coupled differential equations for flow and heat and species transport in porous media.

3.3.1 The crystalline around the German Continental Deep Drilling (KTB)

Based on the structural and petrophysical analysis of the seismic and drilling data of the KTB (Fig. 5 and Fig. 7a and 7b) a 3D flow model can be established (Fig. 8a), considering topographic head as a natural driving force. Although flow velocities are small in these dense crystalline rocks, this simulation clearly indicates predominate flow along faults. Once the dominant flow regions are identified, a local geothermal installation with an injection and production can be simulated. Here, we attribute on a small scale highly anisotropic permeabilities in the fault zone as identified on drilled samples (Fig. 8b) The resulting flow field is shown in Fig. 8c and the temperature at the producer over time is analyzed according the sustainability (Fig. 8d).

3.3.2 The Northern German Sedimentary Basin

While the KTB histograms were used to attribute rock properties to fractured or lithologically different rocks, we follow a different approach in the case of the Northern German Sedimentary Basin (Fig. 3). We attribute rock properties based on the histograms in Fig. 7c and 7d stochastically using the geostatistic method of Deutsch and Journel (1998) considering appropriate correlation lengths. In this way we construct a large number of Monte Carlo (MC) realizations, each equally likely to reflect the natural conditions (see Fig. 9b and 9c). In this paper, we demonstrate how stochastic modeling can be used to reduce the degree of uncertainty in temperature. In an accompanying paper (Vogt et al. 2013, this issue) we show how this approach can be used to reduce the risk for a geothermal installation.

In a first step, bottom hole temperature (BHT) data from a number of shallow wells and the method of Bayesian inversion are used to determine the specific heat flux required at the bottom of the model.

Bayesian inversion is also a modular part of the SHEMAT-Suite code. It uses an objective function of the type (Tarantola, 2004)

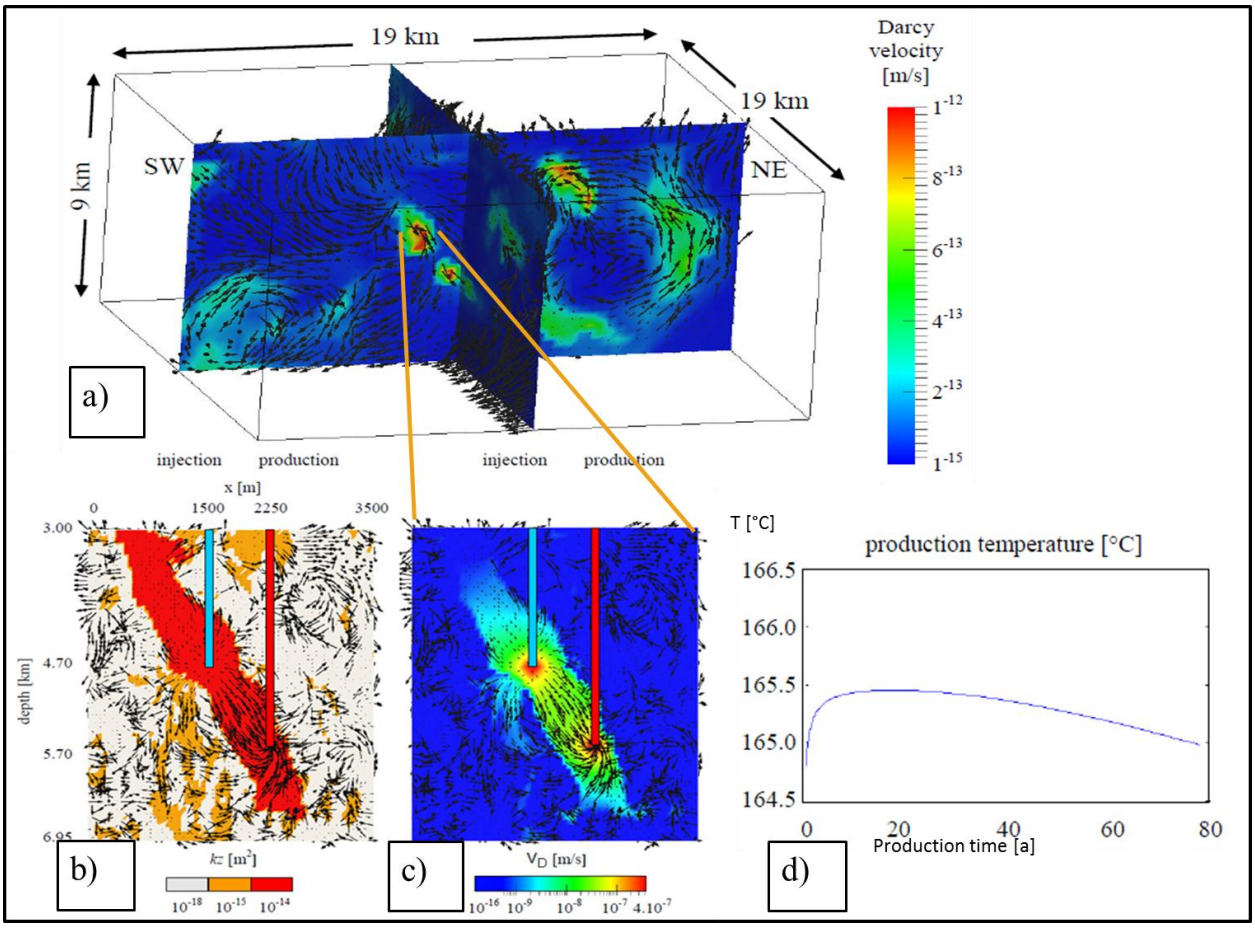


Figure 8: Flow simulation for the KTB case (Szalaiová 2012): a) flow in the large model, note the flow along the fault; b) detailed permeability in the main fault, and test layout for injection and production boreholes; c) calculated flow pattern; d) variation of production temperature with time.

$$\Theta = (d - g(p))^T C_d^{-1} (d - g(p)) + (p - p_a)^T C_p^{-1} (p - p_a) = Min \qquad [1]$$

p is the vector of system parameters, $g(p)$ the predicted system response (calculated by SHEMAT-Suite), and d is the data vector. C_d and C_p are the a priori data and parameter covariance matrices, respectively, which need to be known. Linearization and differentiation of the objective function Θ yields an iteration scheme (with k here as the iteration index) for the parameter vector p

$$p^{k+1} = p^k + [J^T C_d^{-1} J + C_p^{-1}]^{-1} \cdot [J^T C_d^{-1} (d - g(p^k)) - C_p^{-1} (p^k - p_a)] \qquad [2]$$

The Jacobian $J_{ij} = \frac{\partial g(p)_i}{\partial p_j}$ is the derivative of the model prediction with respect to the various parameters and is determined in SHEMAT-Suite by automatic differentiation (AD) (Bischof et al. 2008).

In this application, we inverted for the bottom specific heat flow assuming constant rock properties and determined a value of 77.7 mW m^{-2} which best fitted the BHT data in a least-squares-sense. In the second step we used this bottom specific heat flow and stochastically attributed rock properties for a number of Mont Carlo realisations, following the histograms Fig. 7c and 7d, and a steady state simulation calculated for each model. For all these simulations the temperature profiles are shown in Fig. 9a as a bundle of coloered lines. Evaluating these results and comparing them to the standard deviation based only on the obervations (thin blue lines in Fig. 9a) reduced the uncertainty range by a factor of three for a temperature prediction at the depth of the target layer from 45 K to 15 K (and even more at greater depths).

3.3.3 Estimating reservoir properties with the Ensemble Kalman filter

As a third illustration we demonstrate the potential of the Ensemble Kalman Filter (EnKF, Evensen 2003; 2009) estimating reservoir properties if transient monitoring data are available. This filtering method is implemented in SHEMAT-Suite and has been used to analyze successfully the permeability distribution between the injection and production boreholes of the geothermal installation at Soultz-sous-Forêts (Vogt et al. 2012). The EnKF is a minimum variance estimator with quadratic error propagation.

As a starting point of the estimation (similar to Monte Carlo modeling) a number of ensemble members are

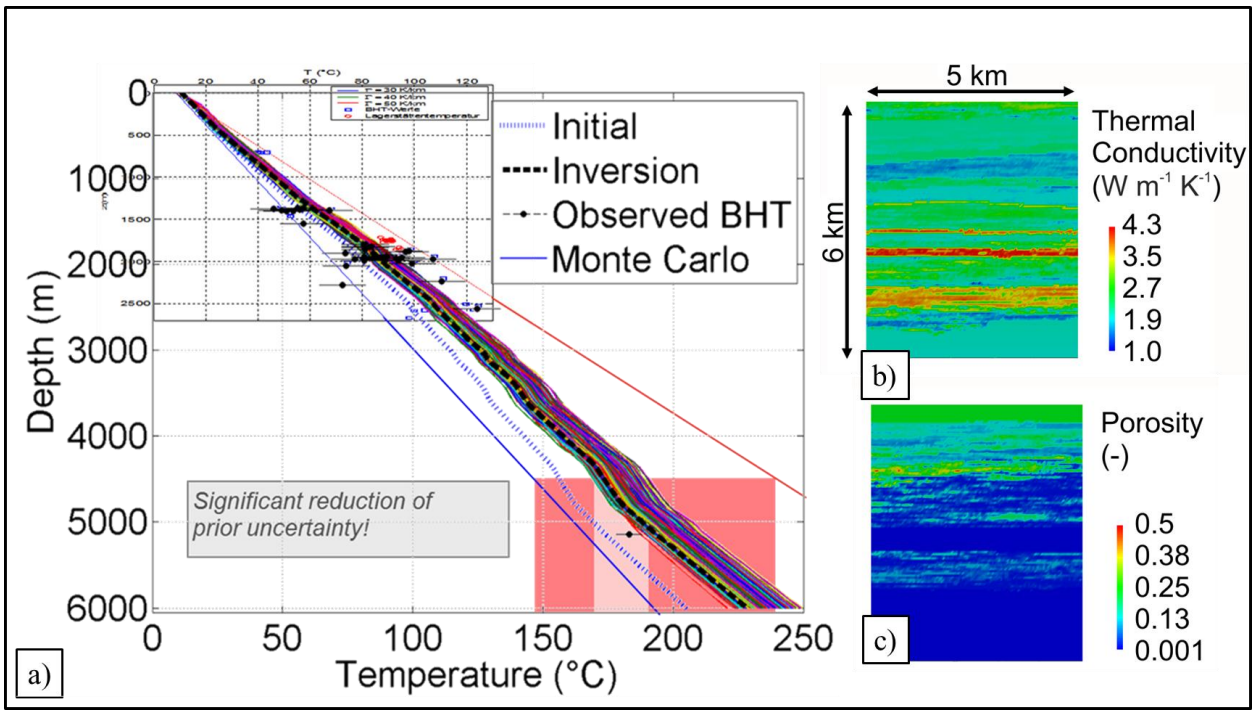


Figure 9: Predicted temperature depth profile in the deep well of a reservoir in the Northern German Basin (see Fig. 3c; after Vogt et al. 2013). Small black dots with error bars are measurements in the shallow wells, the thin blue and red lines indicates the uncertainty range based on the measurements and a best and worst case estimate, colored lines show the results of the Monte Carlo ensemble with stochastically varying thermal conductivity and porosity according to the histograms (see e. g. Fig. 7c), b and c) thermal conductivity and porosity distribution of one randomly chosen Monte Carlo realization.

defined which reflect the probability distribution of the dynamic state variables and the reservoir properties. This is followed by a tow step procedure: the first step comprises a comparison between a forcast for a number of observations and the observation themselves. The second assimilation step propagates the information from the observation points through the non-linear system, weighted by the probability distribution of the actual state of the system. The spatial distributions of the variances are measures for the reliability of the estimated state or property fields.

Here we show a synthetic test example of a sedimentary reservoir at a depth of 2500 m with horizontal dimension of 500 m x 500 m. A synthetic “true” permeability distribution (Fig. 10a) is created based on a histogram similar to the one shown in Fig. 7. Then we performed a blind test based on an assumed tracer injection in a borehole in the center of the reservoir and monitoring of the chemical concentration at some production wells, for identifying areas of high permeability, i. e. of favorable connectivity for a geothermal doublet installation. The tracer concentration at these production wells, superposed with some noise is then used as data for an EnKF estimation of the permeability field. Favorable location for the production wells are then proposed by a “blind test expert” who identifies areas of high connectivity.

At first, permeability is completely unknown. Therefore we start with a setup with production wells close to the lower left and upper right corners .Fig. 10b shows the result of the EnKF estimation after the first step: the lower figure shows the estimated permeability field and the upper figure the standard deviation of the ensemble. The area between the boreholes is clearly resolved best, showing increased permeability around the borehole in the lower left corner. However, the region with highest permeability is not well resolved. In the second step, we added two additional production wells in the lower left quadrant, repeated the numerical tracer injection test and again estimated the permeability field with the EnKF (Fig. 10c). This already yields an acceptable estimation of the highly permeable areas in the reservoir. The estimation can be improved further with a fifth production well and two monitoring slim holes between the injection and the two production wells to the left.

3. CONCLUSIONS

In the cooperative MeProRisk project, we demonstrate how new methods developed and refined in exploration seismology, petrophysics, parameter estimation and numerical reservoir management are combined for optimizing exploration of and production from reservoirs. Practical application of our methods to a target area for geothermal energy production will improve iteratively the information on reservoir geometry including faults and fissures. It

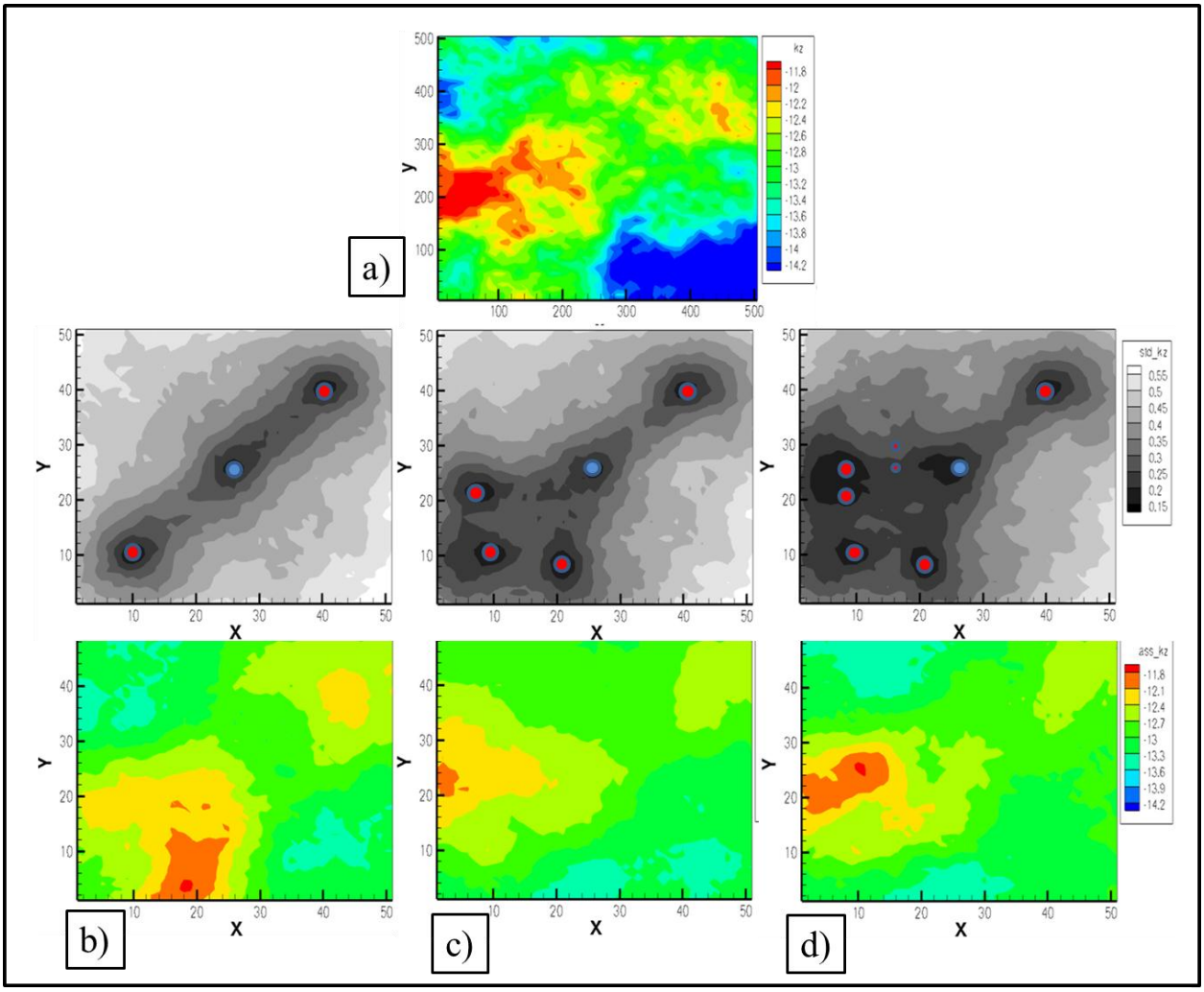


Figure 10: Synthetic test case for estimation of the reservoir permeability with the EnKF assuming a tracer experiment with injection in a central borehole (blue dot) (Klein, 2013 pers. com.): a) synthetic "true", b) - d) estimation based on two, four and five production wells (large red dots), upper figure is standard deviation, lower figure is estimated permeability, respectively, in case d) two passive slim holes are assumed additionally (small red dots). (Axes lengths: a) in meter, b) - d) in grid points.)

allows robust estimating of rock physical properties and their uncertainties, and provides reliable simulations of fluid flow and heat recovery with improved estimation of uncertainty.

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