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ELECTRICAL RESISTANCE TOMOGRAPHY FOR MONITORING OF UNDERGROUND COAL GASIFICATION

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ABSTRACT

Monitoring of underground coal gasification (UCG) is essential for optimal process control and risk mitigation. We present the use of electrical resistance tomography (ERT) to monitor subsurface cavity growth, which takes advantage of the drastic changes in the electrical resistivity of coal caused by UCG. Electrical resistivity of coal can vary many orders of magnitude from 10^6 Ohm-m for dry coal to less than 1 Ohm-m for hot (> 650 °C) carbonized coal. ERT is a 3D electrical resistivity imaging technique with fully autonomous data acquisition that makes near real-time monitoring possible and affordable. ERT electrodes can be collocated with other downhole tools such as pressure and temperature sensors. Therefore, ERT shows strong potential as an effective and low-cost UCG monitoring tool.

We constructed an electrical resistivity model based on the geology and coal seam parameters of the Wulanchabu UCG project site of ENN, China. A UCG process was simulated in this model and expected ERT measurements were modeled. The synthetic ERT data were inverted to infer the geometry of the UCG cavity and surrounding thermal impact. The deterministic inverse method produced accurate images of the cavity geometry and thermal effects. The stochastic inversion is a promising data integration method because it is capable of jointly inverting disparate data and providing solution uncertainties.

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Introduction

Monitoring of underground coal gasification (UCG) helps optimize the process management and mitigate the risk such as subsidence and groundwater contamination. A UCG operation is full of uncertainties because complicated chemical, thermal, geomechanical and hydrological processes take place in the subsurface (Burton et al., 2007). An effective monitoring program provides better understanding of the processes and results in a more efficient and responsible operation. An effective monitoring plan and implementation may also accelerate permitting and shield against liabilities.

Conventional UCG monitoring programs were often limited to chemical process monitoring and selected surface or down-hole point measurements (Metzger and Britten, 1988). These included measurements of flow rate and composition of injected gases (air/oxygen/steam), temperature, pressure, syngas composition and heating value. Subsurface temperature changes were monitored by thermocouples in wells. These monitoring efforts provided vital information on the process performance.

As environmental effects are also a concern, groundwater and subsidence have also been monitored. During the Hoe Creek II experiment in Wyoming, a number of wells were instrumented with extensometers, shear-strips and piezometers for monitoring of overburden subsidence (Stephens, 1981). A comprehensive groundwater monitoring program was implemented during the Rocky Mountain I experiment in Wyoming with both spatial and temporal coverages (Metzger and Britten, 1988).

A variety of methods have been tested to infer burn front location and cavity geometry, as these are critical for both process control and avoiding environmental effects. As the electrical resistivity of coal depends strongly on its thermal history (Duba et al., 1978), electrical and electromagnetic methods such as HFEM, EM induction tomography (EMIT) and controlled source audio magnetotellurics (CSAMT) have been extensively tested

The high frequency electromagnetic (HFEM) imaging method located the position of the burn front to within 1 m during the Hoe Creek II and III experiments in Wyoming (Duba et al, 1978). This imaging system used HFEM radiation of 1MHz to 100 MHz between boreholes up to 25 m apart. The drawback is that both transmitter and receiver must be lowered or raised in open boreholes manually, making HFEM data collection labor intensive. During the UCG experiment in Centralia, Washington, the cavity growth was monitored with thermocouples, time-domain reflectometry (TDR), controlled source audio-magnetotelluric (CSAMT) and total coal consumption (Cena et al., 1984). TDR measurements of undamaged cable length provided primary evidence on the location of the burn front but it is a point measurement. CSAMT is a surface-based geophysical method and it doesn't have a good resolution at a depth below 100m (Didwall and Dease, 1983).

The success of these electrical/electromagnetic geophysical techniques lies in the changes in resistivity with thermal history of coal. Below 600°C coal loses water and becomes less conductive than water saturated coal (Figure 1). Above 600°C coal can be 100,000 times more conductive than

water-saturated coal, i.e., from 0.001 S/m to 100 S/m. At temperatures above 300°C, pyrolysis begins and the relative carbon content of the residue increases, enhancing its conductivity dramatically. As a UCG cavity is expected to reach these temperatures, electrical resistivity is clearly an effective indicator of cavity conditions.

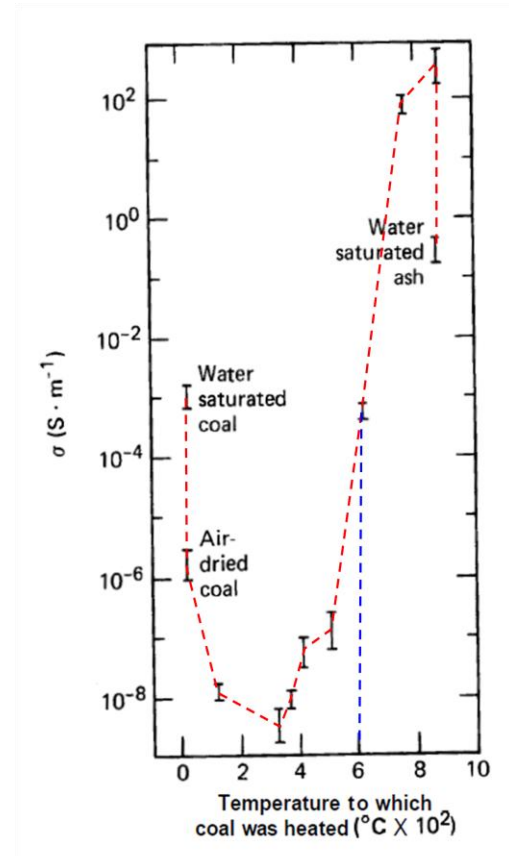


Figure 1. Coal conductivity versus temperature (adapted from Duba et al, 1978). Conductivity was measured at 1kHz.

ERT is a proven tomographic technology for monitoring of subsurface processes such as vadose zone water movement (Daily et al., 1992), steam injection (LaBrecque and Yang, 2001) and in-situ air sparging (Yang et al., 2001). Most recently time-lapse ERT has been used to track injected CO₂ plume growth and movement at depths of over 3200m (Carrigan et al., 2009). As CO₂ displaces conductive brine, it produces strong resistive anomalies.

ERT is best suited for UCG monitoring. First, ERT is very sensitive to gas/fluid saturation and temperature changes that are important variables of a UCG process. Second, an ERT sensor or electrode has a very low cost and may be collocated with other sensors. Finally, ERT data collection can be automated for autonomous monitoring. These advantages make near real-time monitoring of UCG with ERT feasible and relatively low-cost.

Once ERT data are collected, they must be inverted to yield estimates of UCG cavity geometry. The standard approach is a deterministic inversion method that solves a least squares optimization problem. This often produces a smooth and inaccurate model. The result also

depends on the starting model. There is no easy way to estimate model uncertainties. Stochastic inversion methods facilitate integration of disparate data, avoid dependence on the starting model and provide rigorous uncertainty estimates of the solution. These uncertainty estimates are useful in an operational setting for risk assessment and decision making.

Our objective is to image resistivity changes around a UCG cavity. We test both deterministic and newly-developed stochastic inversion approaches. Our novel MCMC stochastic inversion algorithm is adapted from Ramirez et al. (2005) with a new UCG sampler to accommodate cavity geometry. It integrates ERT, cavity volume estimate and coal seam boundary data in three cascading stages. The preliminary inversion results are compared and analyzed to determine the effectiveness of ERT for delineation of a cavity.

SYNTHETIC RESISTIVITY MODEL

The tests were run on a synthetic baseline resistivity model based on the site geology of the Wulanchabu UCG project by ENN, China. We assigned empirical resistivity values to lithofacies and coal seams. Two coal seams (200 Ohm-m) are located at a depth approximately between 260m and 285m (Figure 2). The 10m-thick lower coal seam from 276m to 286m was targeted for this study.

For monitoring of cavity growth, we embedded a cavity in the lower coal seam (Figure 3). The gas-filled resistive cavity is masked by conductive char (1 Ohm-m) and hot wet coal/rock (10 Ohm-m) and it is not detectable by the ERT method. The baseline model in Figure 3 showed discontinuities of multiple layers, which pose challenging for ERT interpretation algorithms.

To simulate 3D UCG monitoring with ERT, we introduced four boreholes with 17 electrodes per borehole for a total of 68 electrodes in the computational model (Figure 4). Two-dimensional monitoring needs only two boreholes and produces a cross-section image. Four boreholes are laid out at the corners of a 30m by 30m square. Electrode spacing is 3m. Any pair of electrodes can be used to inject electric current and one or more pairs of electrodes measure the voltages simultaneously. A large number of transmitter-receiver combinations can be programmed. We chose the dipole-dipole electrode array and produced about 2000 synthetic measurements. We created two synthetic data sets with and without the embedded cavity using the in-house MULTIBH ERT modeling code described by LaBrecque et al. (1999).

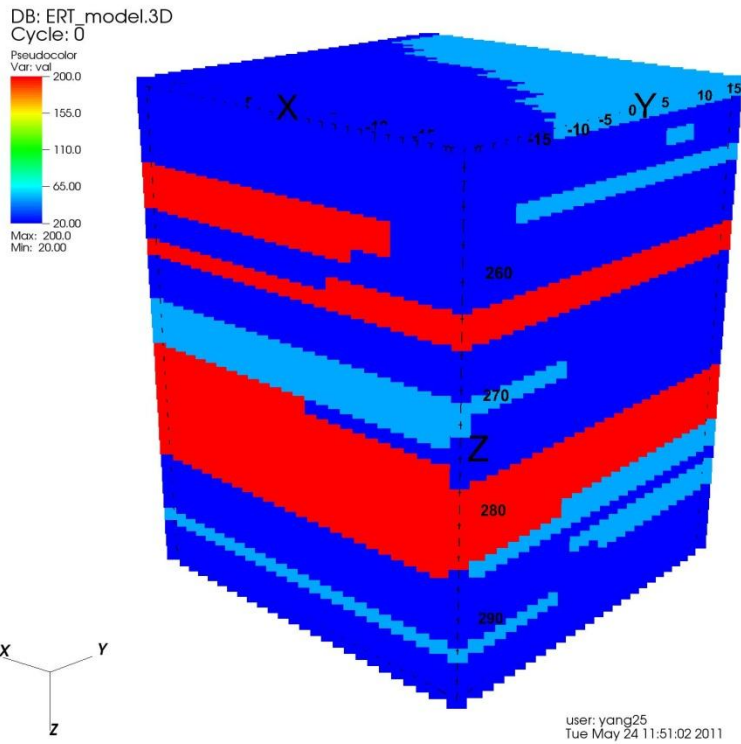


Figure 2. The synthetic baseline resistivity model converted from Wulanchabu lithology model. The red layers are coal seams.

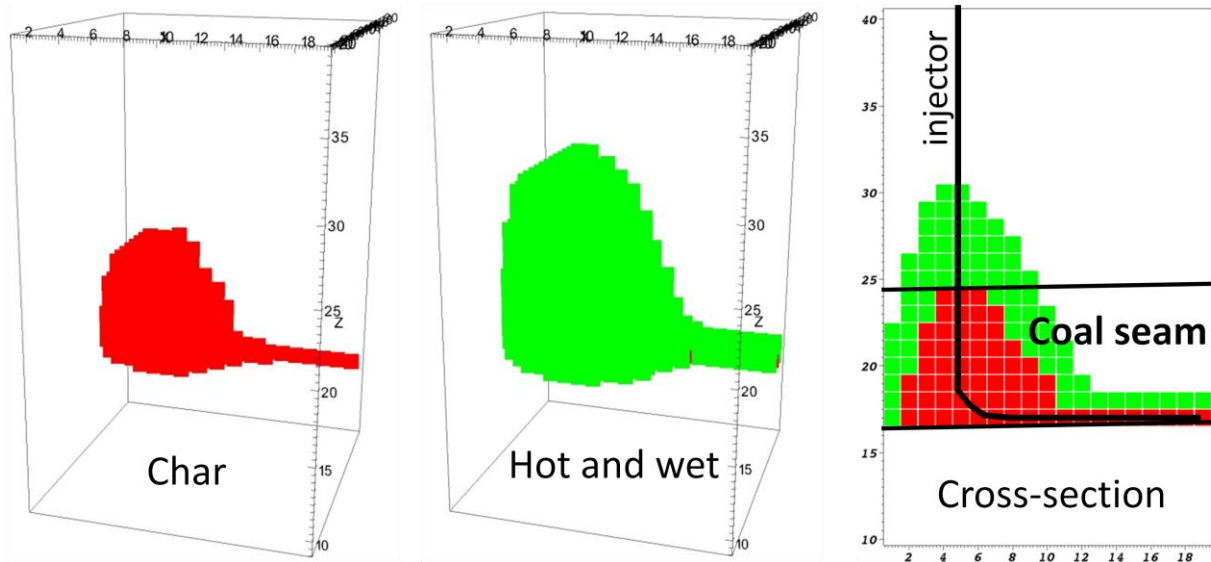


Figure 3. A cavity is embedded in the lower coal seam and the thermal effect penetrated into the overburden. The red region is a conductive (1 Ohm-m) char-surrounded cavity and the green part is less conductive (10 Ohm-m) hot and wet rock/coal.

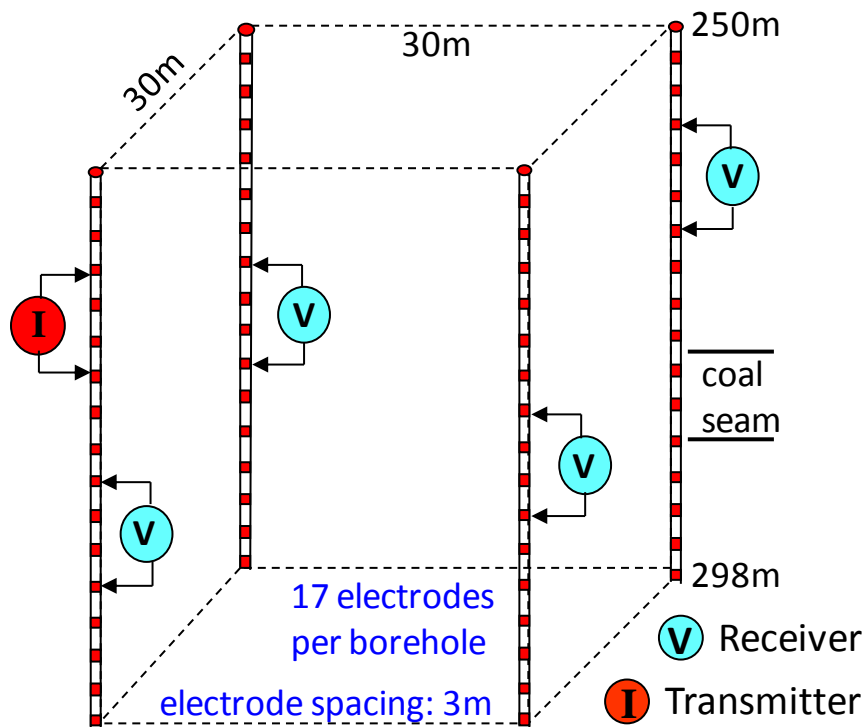


Figure 4. Borehole and electrode layout for 3D UCG monitoring with ERT.

METHODS

Both deterministic and stochastic inversion methods were tested in this study. ERT data are routinely processed in a deterministic inverse approach by solving a least squares optimization problem. A deterministic inversion method often produces a smooth model whose response best fits the observed data to a pre-defined statistic. The optimization process is sometimes trapped by local minima. A realistic and accurate model is rarely achieved. Stochastic inversion methods are an attractive alternative to the conventional deterministic inversion.

Our deterministic inversion approach uses a finite difference forward model and a least squares smooth model inverse algorithm described by LaBrecque et al. (1999). The modeling code is dubbed MULTIBH. The objective of UCG monitoring is subsurface resistivity changes induced by UCG processes. Instead of inverting baseline and monitor data sets independently, we may invert a difference data set between monitor and baseline data (Labrecque and Yang, 2001) or a ratio data set derived from baseline data, monitor data and a forward solution of a homogeneous half space of 1 Ohm (Ramirez et al., 2005).

Instead of looking for the “best” model, a stochastic inverse algorithm maps the entire model space by finding a large number of models that fit the data to varying degrees and characterizes posterior probability distribution of the model effectively. Stochastic methods provide rigorous uncertainty estimates of the solution that are needed in a decision making process. In addition,

stochastic inversion offers a convenient mechanism that facilitates integrating disparate data and imposing various constraints.

Ramirez *et al* (2005) developed a Markov Chain Monte Carlo (MCMC) approach to invert ERT data for mapping subsurface plumes. This MCMC stochastic inversion algorithm is based on Bayesian inference framework and it is driven by the Metropolis algorithm, an importance sampling method. This MCMC method incorporates resistance measurements, forward modeling solutions and a priori knowledge to produce realistic subsurface resistivity distribution.

The Stochastic Engine (SE) described by Ramirez et al. (2005) was used to carry out the stochastic inversion of ERT data. SE was made flexible for integration of new data and modeling codes. Our approach consists of three cascading stages for jointly inverting ERT ratio data, coal seam layer boundaries and volume of coal consumed estimated from mass balance (Figure 5).

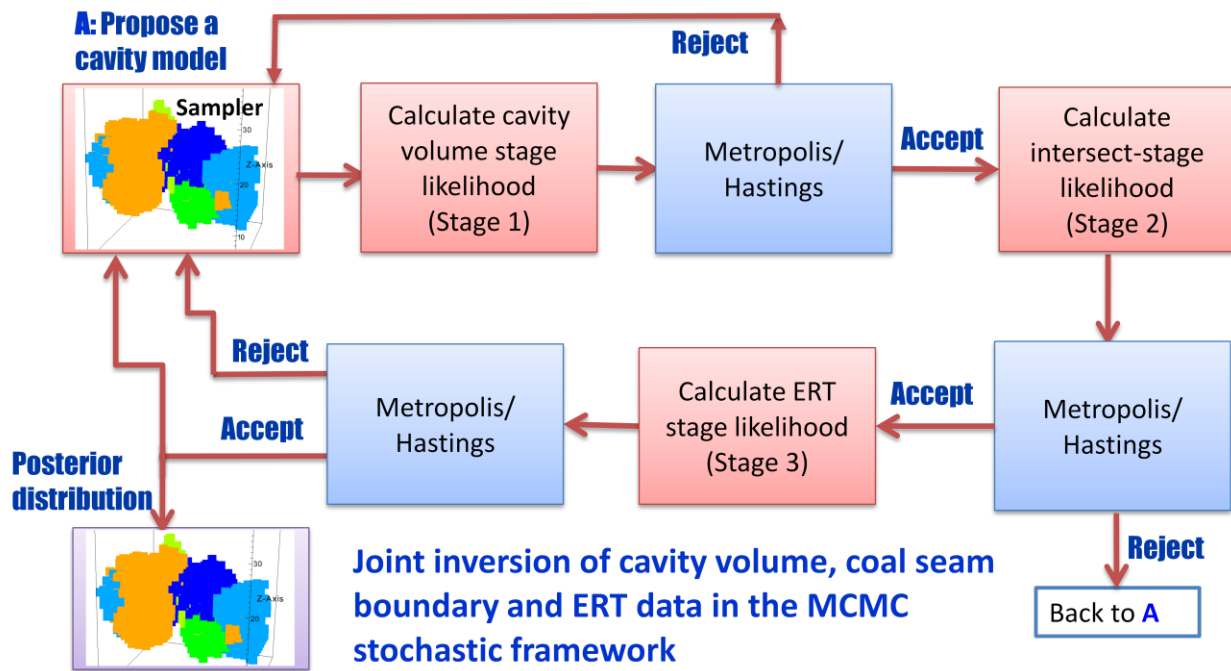


Figure 5, Flow diagram of Markov Chain Monte Carlo (MCMC) stochastic inversion.

A new UCG sampler was developed to model a cavity with connected ellipsoids. An initial resistivity model of a UCG cavity is randomly proposed by the UCG sampler (Figure 6). It is modeled by multiple connected upright ellipsoids that are also connected to the injector individually. At any iteration, one ellipsoid is randomly chosen for one of these actions: translation, rotation, inflation, deflation, change of resistivity category and deletion. All ellipsoids initially created cannot be deleted. A new ellipsoid may be added to the ellipsoid network but it is not required for a new ellipsoid to intersect the injector. Any successful move must maintain that all ellipsoids are connected and every initial ellipsoid is also connected to the injector.

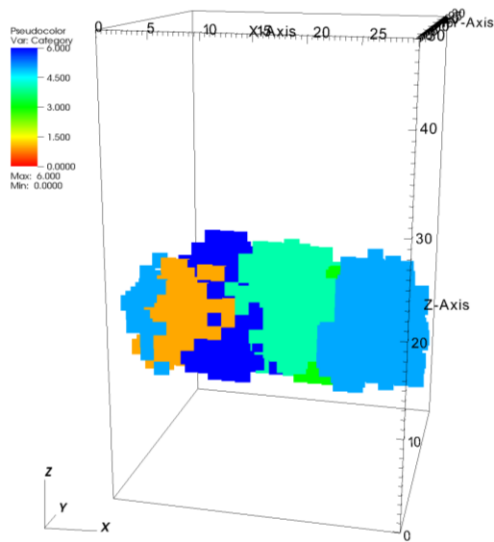


Figure 6. Initial cavity resistivity model randomly proposed by the UCG sampler. The color scale corresponds to the category index of resistivity ratios (1.0, 0.01, 0.03, 0.1, 0.3, 3.0, 10.0).

RESULTS

The deterministic inversion reveals resistivity changes relative to the baseline model. Our difference inversion algorithm resolved the cavity size and shape accurately (dark red color in cross-section image of Figure 7). There is a clear indication of thermal impact (light red and yellow colors in cross-section image of Figure 7).

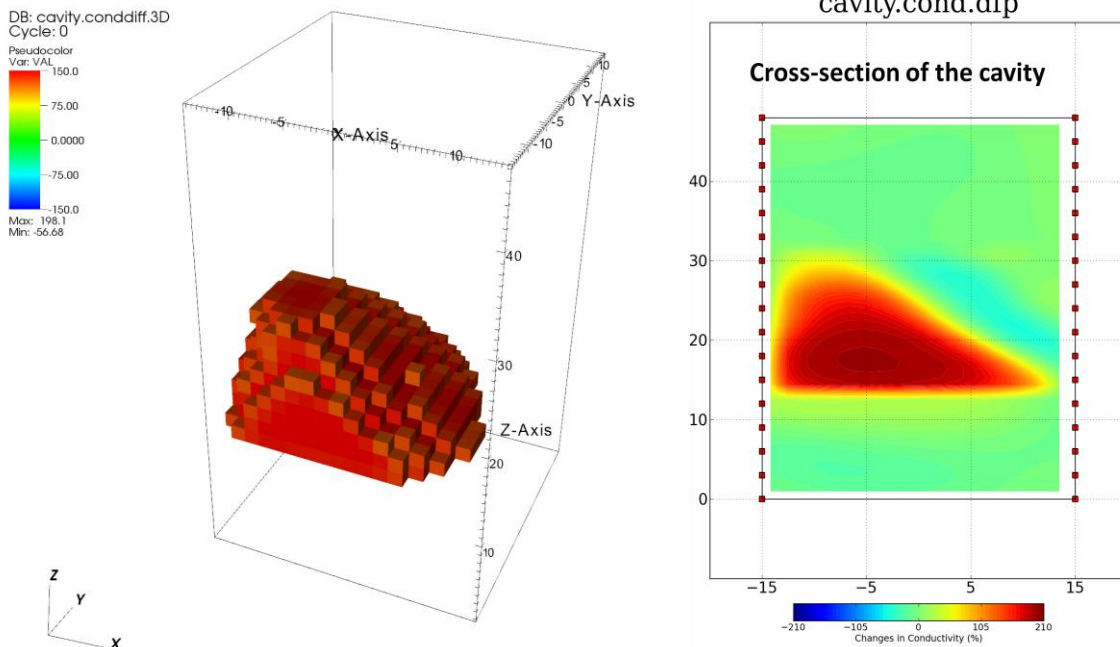


Figure 7. Preliminary result of deterministic inversion of a synthetic difference data set. To the left is the reconstructed 3D cavity image and to the right is the vertical cross section along the injector.

The resistivity models in the posterior distribution of stochastic inversion are analyzed using a k-median cluster analysis tool (de Hoon et al., 2010). The centroid of a cluster with the highest sample frequency is shown in Figure 8. This high-likelihood model agrees roughly with the synthetic model in Figure 3. The massive orange body represents the more conductive part of the inner cavity. The thermal effect of the less conductive outer part is also visible on the image but not fully covers the inner cavity.

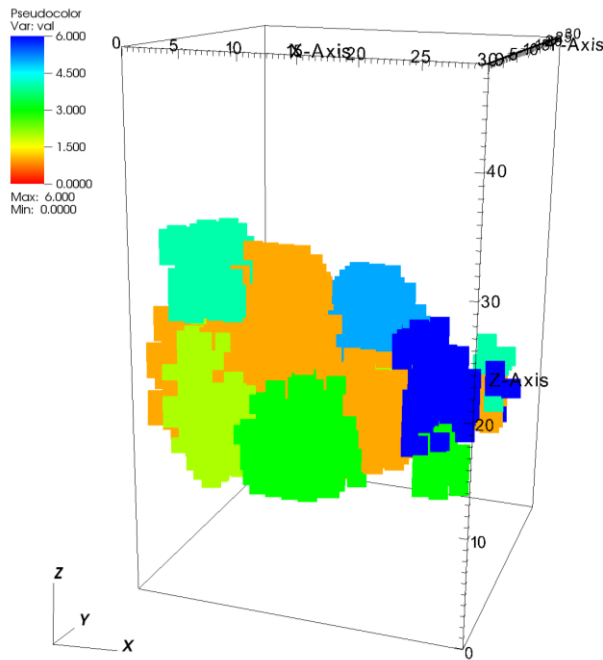


Figure 8. The most likely resistivity model found by stochastic inversion with a probability of 46.6%. The color scale corresponds to the category index of resistivity ratios (1.0, 0.01, 0.03, 0.1, 0.3, 3.0, 10.0).

CONCLUSIONS

Our synthetic model studies demonstrated that ERT can detect the conductive UCG cavity and its associated thermally altered zone. The resistivity model reconstructed from the deterministic inversion of ERT difference data matches the overall features of the synthetic model resolves the size and shape of the cavity accurately. ERT monitoring can potentially detect leakage of hot syngas and hot fluids from the cavity.

Joint inversion of ERT ratio data set of monitor to baseline measurements, coal seam boundary and volume of coal consumed using MCMC stochastic inversion method delineated the cavity shape and showed some resolution of resistivity contrast between the inner cavity and outer thermal effect. The stochastic approach is a promising data integration method.

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