

## Stochastic Joint Inversion Modeling Algorithm of Geothermal Prospects

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### ABSTRACT

A stochastic joint inverse algorithm is applied to prospect evaluation. The goal is to predict fluid flow and temperature distributions in the subsurface that are most consistent with available geologic, hydrological, and geophysical data. The approach uses a modified Monte Carlo global search algorithm. Currently, the algorithm begins with an initial conceptual model descriptive of structural (geology), parametric (permeability) and hydrothermal (saturation, temperature) characteristic of the system. Aspects of this model are allowed to vary during the inversion process using (*a priori*) estimates of conceptual model uncertainty and constraints provided by MT, temperature measurements, and surface resistivity measurements. The algorithm has been tested on a geothermal prospect located at Superstition Mountain, California and has been successful in creating a suite of models compatible with available data. A typical inversion evaluates several thousand possible models and provides *a posteriori* estimates of model uncertainty. We are testing the use of sensitivity analyses to better identify critical uncertain variables, lower order surrogate models to streamline computational costs, and value of information analyses to better assess optimal use of related data.

### 1. INTRODUCTION

Geothermal exploration seeks to find commercial sources of geothermal energy. This, in turn, requires finding and characterizing potential production sites with sufficient heat, water, and hydraulic permeability. Typically, investigations of a specific prospect begin with near-surface or aerial data collection, which is followed by exploratory drilling, and then, if successful, production drilling. This work seeks to maximize data analysis from the first stages of exploration to yield a robust model of the prospect that includes predicted subsurface temperatures and permeability. It combines hydrothermal flow simulation with geophysical inversion techniques. The goal is to improve prospect evaluation, which will aid decisions on development and possible future drilling sites. More specifically, we have two main goals: 1) to identify one or more feasible models that best match observable data, and 2) what is the likelihood that any feasible model may represent a significant geothermal resource?

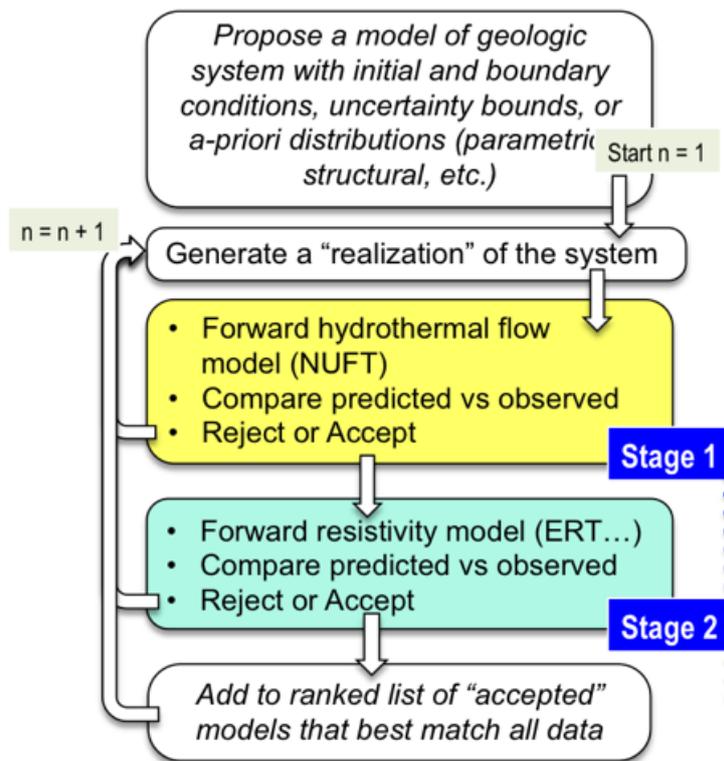
We have been working on a joint inversion methodology to utilize multiple geophysical, thermal, and hydrological data sets. Previous papers [Mellors et al., 2013; Tompson et al., 2013] have outlined our basic approach. This paper reports on improvements made to the algorithm, which include the capability to model MT and explorations into the use of sensitivity analysis and surrogate models to decrease computational load. Here we briefly summarize progress made so far.

The approach uses a generalized Markov Chain Monte Carlo (MCMC) inversion process (Mosegaard and Tarantola, 1995), which uses a stochastic approach (Figure 1). The procedure is based on that used in Ramirez et al., (2005; 2011). This algorithm possesses several advantages: it is flexible, searches the global solution space defined by the stochastic variable distributions, and provides robust uncertainty estimates. The results are expressed as a range of models along with associated estimates of uncertainty. This aids in providing a quantitative evaluation of the prospect.

The initial application is a geothermal prospect located in the western Salton Trough in California, adjacent to Superstition Mountain (Figure 2), and currently under investigation by the Navy geothermal program (e.g. Bjornstad et al., 2006; Tiedeman et al., 2011). Available data includes vertical temperature profiles observed in a set of three exploration "NAFEC" wells (Figure 3), geologic data, and MT measurements.

We have developed an initial 3-D geologic model defining the structural geometry of the prospect. Uncertain material properties such as permeability, porosity, and heat capacity are allowed to vary in the simulation process, as well as certain structural characteristics such as the extent and properties of a postulated fault zone. The simulation algorithm first assumes *a priori* statistical distributions for these uncertain properties and structural characteristics and then a staged MCMC approach follows, which is intended to find a suite of solutions consistent with observed temperature and resistivity data.

Results are presented as a ranked set of all sampled models along with inferred *a posteriori* probability distributions. This process is computationally intensive and we are exploring the use of sensitivity and reduced order model to reduce computational effort and expand the solution space. In this study we focus on the linked hydrothermal/MT inversion and the sensitivity study, as these have not been presented previously.



**Figure 1: An outline of the stochastic inversion process.**

## 2. METHOD

As shown in Figure 1, our inversion algorithm applies a Monte Carlo-Markov Chain (MCMC) global search approach to carry out a staged inversion of the different data sets. Joint inversion is accomplished by cascading computational stages, one for each data set. In order for a particular geologic and hydrothermal model to be included in the final answer, it must be accepted by all of the stages. Specifically, in the first stage of the MCMC process, a 3-D hydrothermal flow model is used to predict equilibrium (steady state) temperature and fluid flow fields under various model realizations, which are then compared to the measured temperature profiles. If a model satisfies criteria from the first stage, electrical resistivity distributions are calculated using the model from the first stage and compared to the observed data, which may consist of either direct resistivity measurements or magneto-telluric (MT) observations. Additional details are available in Tompson et al. [2013].

In our test case, the basic geologic model was based a geothermal prospect near Superstition Mountain, California (e.g., Bjornstad et al., 2006; Tiedeman et al., 2011, Tompson et al, 2008). The initial hydrologic model parameters include permeability, porosity, temperatures, and resistivity properties for each geologic unit, along with temperature and pressure boundary conditions. We also assume a specific salinity for the water. In the first stage, a thermal/hydrological model is defined and allowed to run to equilibrium. The predicted temperatures are each well location compared to observed values. If the fit is acceptable according to the MCMC criteria, then the model is passed to the next stage for comparison with observed MT data where a comparison with data is repeated. If acceptable, the results are saved.

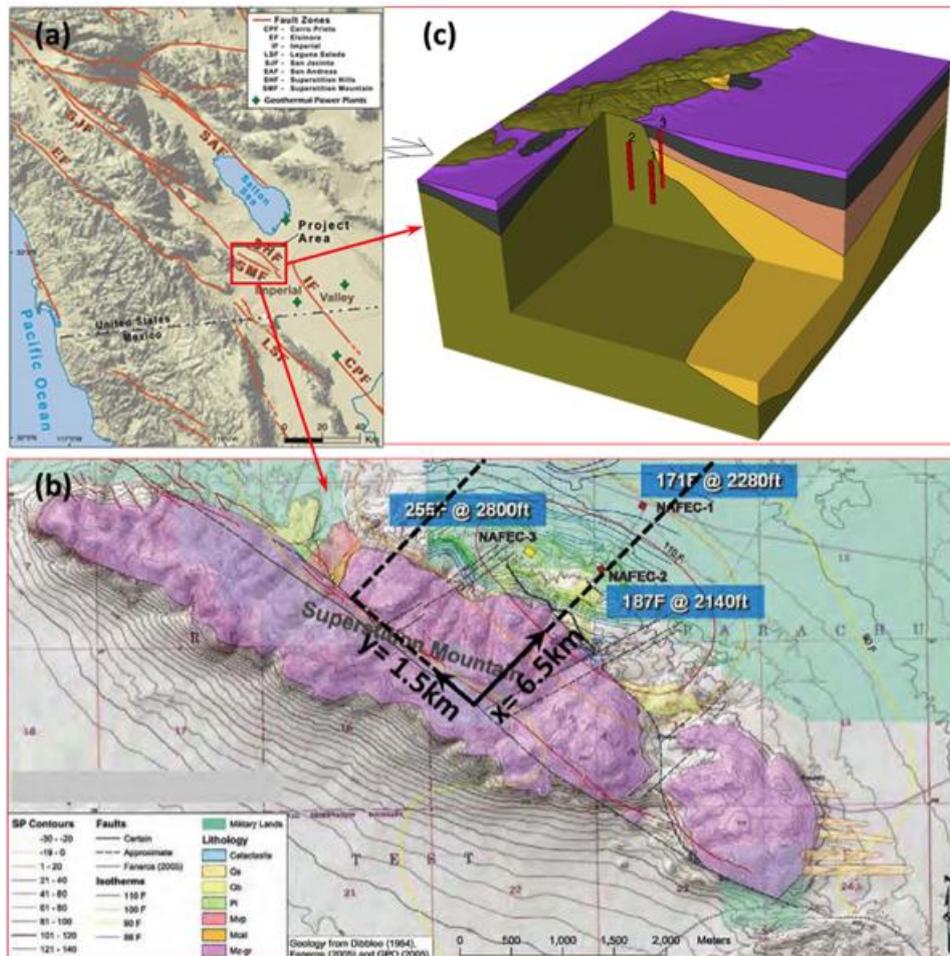
The stochastic inversion framework is written in Python and incorporates various compiled forward codes for each modeled step of the process. We have adapted hydrothermal fluid flow, DC resistivity, and MT resistivity models into the current version of the framework. Fluid and heat flow are simulated using NUFT (Nonisothermal, Unsaturated Flow and Transport), a 3-D multi-phase hydrothermal flow and transport model based upon an integrated finite difference discretization (Nitao, 1998, 2000). Electrical resistivity is simulated using Multibh, a 3-D finite difference forward modeling code that predicts electrical resistance for arbitrary electrode configurations and electrical resistivity models (LaBrecque et al., 1999). MT forward response is adapted from the 2D forward code in the Occam inversion package (e.g. deGroot-Hedlin and Constable, 2004).

For a full inversion, we typically run four MCMC iterations (‘Markov chains’) in parallel. Each set of iterations tests on the order of 5,000 trial models. The major constraint is the NUFT model, which takes most of the computational time. NUFT is a parallel code, but does not scale well. Analysis of the results focuses on the top 10% models and we have also tested the use of cluster analysis to examine the distribution of solutions.

### 2.1 Application to Superstition Mountain prospect

Figure 2 shows a location map, geologic map, and 3D schematic model used for the preliminary applications of the hydrothermal flow and electrical resistivity models. The model used for the inversion is a rectangular parallelepiped oriented perpendicular to the strike of the Superstition Mountain structure. It is 1.5 km wide and extends approximately 6.5 km to the northeast and to a depth of 3.2 km. The domain has been chosen to incorporate the three ‘NAFEC’ wells that were drilled to depths between 600 and 1000 m (~2000 to 3500 ft). Geophysical, lithological, and temperature logs were obtained in each borehole (Figure 3), although no water level or water sampling data were taken. The temperature profiles obtained in each well differed significantly. They suggest

geothermal circulation underlying a shallow zone of conduction-only heat flow in NAFEC-3, conduction-only heat flow in NAFEC-1, and a mixture of the two scenarios in NAFEC-2. Maximum measured temperatures in the wells ranged from 77° to 121°C (171° to 250°F). The raised temperatures, conduction-like profile, and observations of hydrothermally altered rock at the surface suggest flow of hot water along permeable faults at depth. MT data is also available from a survey conducted in 2006.



**Figure 2: Location map and model of prospect. The dashed line indicates the outline of the model.**

A structural and lithologic conceptual model was constructed based on the available data (Figure 4). This model is considerably simplified and should be considered an approximation of the actual structure. At the west end is faulted granitic basement bounded by Miocene and Tertiary clastic deposits to the east. A northeast trending fault is inferred near the NAFEC-2 well. Northeast trending faults occur in the region (e.g. Elmore Ranch fault) and the assumption is not unreasonable. However, more recent Lidar data suggests that a northwest trending fault, parallel to the Superstition Fault, may exist in the location (Unruh et al., 2013). We note that in most geothermal exploration, both data and time are limited and hence most models will be approximate and perhaps incorrect. One of the goals of the inversion is to distinguish quickly between feasible and infeasible models.

For the hydrologic model, we assume saturated conditions throughout the entire model depth. We recognize that the actual water table likely lies at a depth between 100 and 120 m (~350 and 400 ft; Dutcher et al., 1972) but including both saturated and unsaturated conditions in the model, while possible, increases the complexity and computational effort. Proper handling of the unsaturated zone will be added in the future to more properly handle surface heat flow. Temperatures are fixed at the top and bottom (27° and 150°C) at the top and bottom of the domain and a slight lateral hydraulic gradient is imposed from the SW to NE.

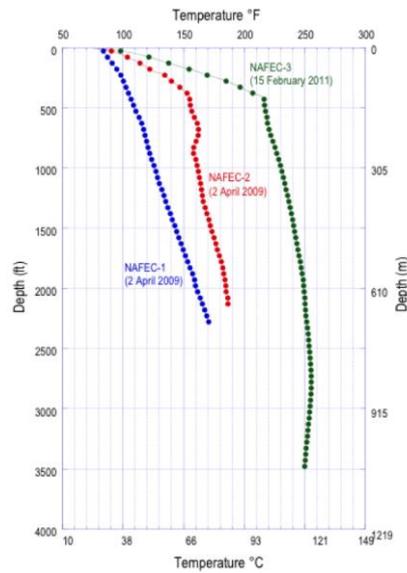


Figure 3: Temperature profiles in the three wells.

The computational mesh design for this problem is challenging for several reasons. The basic mesh for the flow model was developed using the commercial Earthvision program, which allows a convenient way to transition from a geologic model to computational grid. However, two additional complexities exist. First, computational effort per trial model should be minimized, as the MCMC process requires thousands of iterations for a suitable solution. Second, the hydrothermal and resistivity models require different grids, as the resistivity mesh needs to extend into the far-field to avoid excessive edge effects.

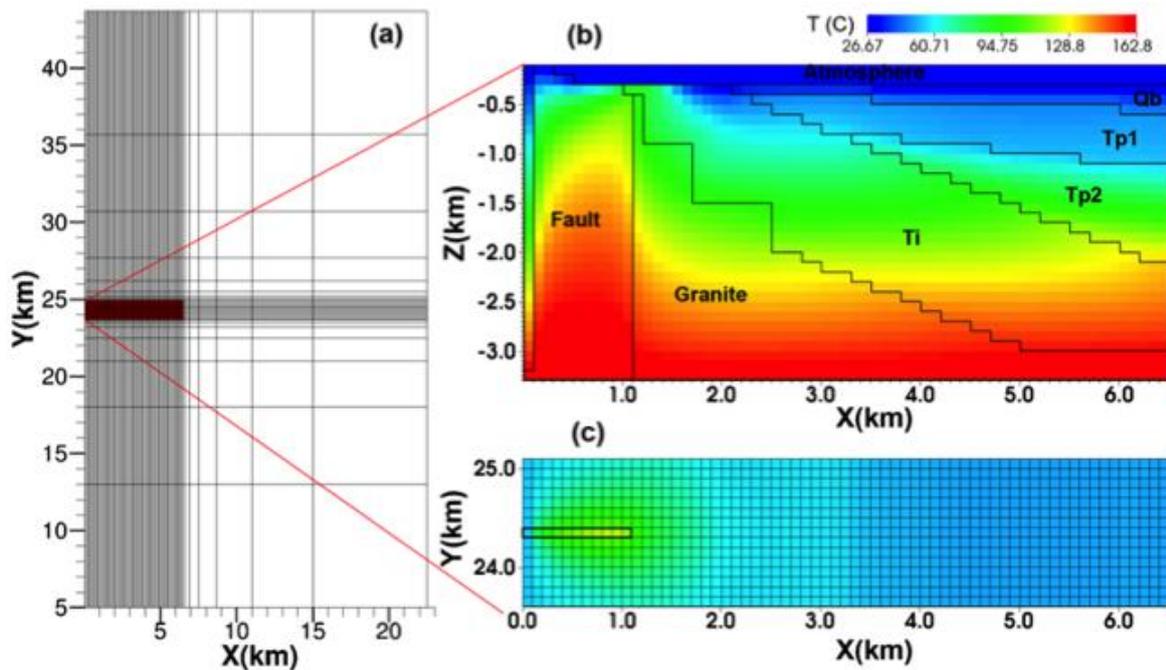
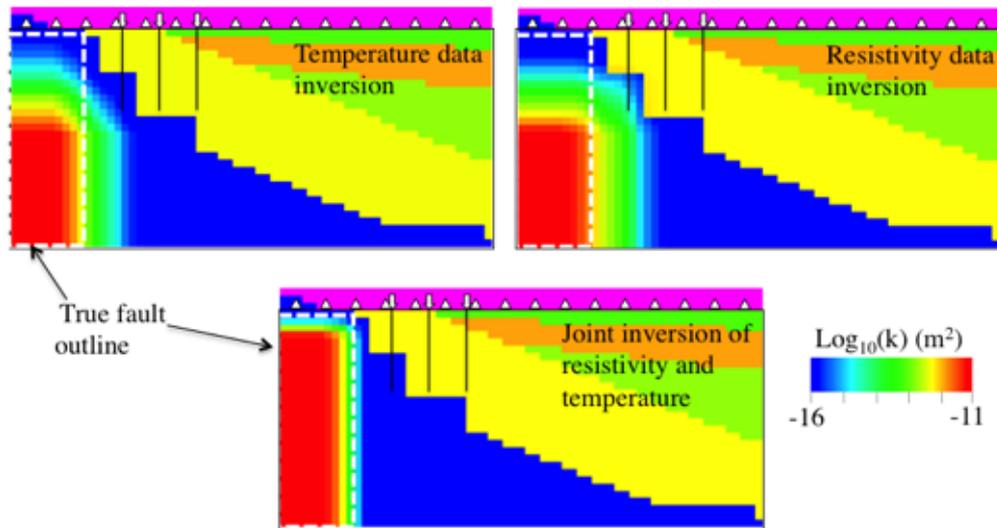


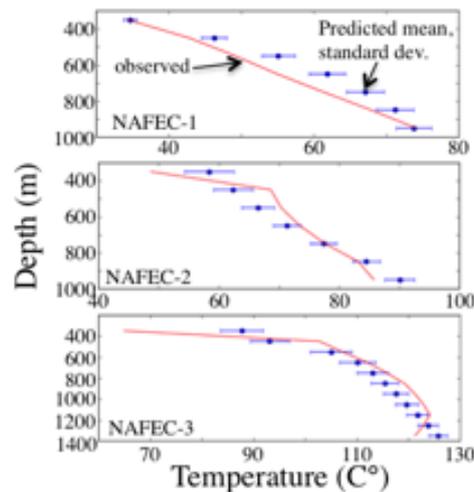
Figure 4: Diagram of the core model showing meshing. Mesh grid spacing is minimum at the location of the three wells and increases towards the edges.

Within the core modeling mesh, both the hydrothermal flow and resistivity models share the same 100-m cubic grid design. For a particular trial, each grid cell belongs to a specific unit (such as granite) to which model-related properties (e.g., permeability, porosity, and heat capacity) are assigned. For some units, material properties are drawn from a prior probability distribution during each replicate simulation in the MCMC process; for others, they are held fixed across all MCMC replicates. Note that changes in the uncertain geometry of the fault zone are accommodated by re-assigning material “fault” properties to the cells comprising the fault. The permeability of the fault zone is allowed to range much higher than that of the surrounding material.



**Figure 5: Examples of inversion of a synthetic model using temperature only (top left), DC resistivity only (top right), and both temperature and resistivity (bottom). The joint inversion with both temperature and resistivity matches the original model well.**

As an example test of the inversion code, we constructed a synthetic dataset by forward modeling one possible variation of a prospect model. Temperature and DC resistivity data were calculated for the model. The synthetic dataset was then inverted to test the inversion algorithm. Figure 5 shows the top 10% of the inversion results (mean values), with the possible fault geometries, which appear to have a color halo around it. The halo represents the range of models and is due to the averaging of different fault geometries. Note that the joint inversion using both temperature and resistivity yields better results than either technique alone. This illustrates the power of the technique to demonstrate the range of possible models. Next we test the inversion using the temperature gradients measured in the NAFEC wells with good results (Figure 6) if a fault near the wells is assumed. Models without a close fault were incapable of matching the data.



**Figure 6: Comparison of inversion results with original model.**

## 2.1 Development of MT and application to real data

For the MT module, we chose to use Occam2DMT, a public domain MT forward and inversion code by Constable et al. (1987). To mimic 3D coverage, we use a series of 2D lines extending from east to west rather than a true 3D representation. We tested several variations of the likelihood function for to find the optimal convergence measure for the complex MT signal. Tests of the module on synthetic models recovered the original data well (Figure 7). In our model, salinity is currently fixed and hence resistivity is primarily a function of temperature.

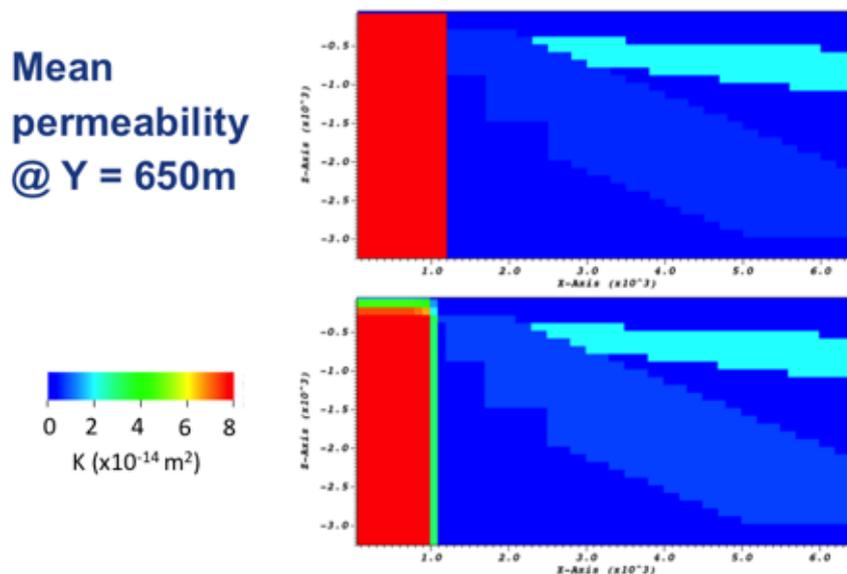


Figure 7: Example of MT inversion with the upper figure showing the original model and the lower figure showing the inverted results.

### 2.2 Sensitivity analysis

As mentioned previously, the MCMC inversion process requires thousands of iterations and a significant computational effort; these tend to constrain the size and complexity of the models used. Our previous efforts treated all variables equally, with no systematic effort to identify the importance of each possible variable. By identifying the most important variables in a problem, we can refine the inversion to focus on these variables alone rather than expend computational effort on searching variables that do not affect the results significantly (Chen et al., 2014). Figure 8 shows a ranking of the importance of the variables for the hydrothermal flow model as employed in this particular example. The results are not extremely surprising but are useful in quantifying variables for future inversions. From this analysis, the fault dimensions are clearly the most important or sensitive variables, as are permeability of the fault and the upper units. The bottom temperature, which is fixed in our simulations, is significant, as is the thermal conductivity of the granite, which strongly depends on porosity. We have also developed and tested a ‘surrogate’ model to provide a fast approximation of the high-fidelity physical hydrothermal flow model calculation. Such models, when properly calibrated and verified, can allow for more complex problem set ups to be addressed (Chen et al., 2014). Surrogate models can be employed in both the sensitivity analysis and inversion portions of this type of analysis, and can also be used in later phases of an exploration effort that involve determining optimal placement and operation of production wells.

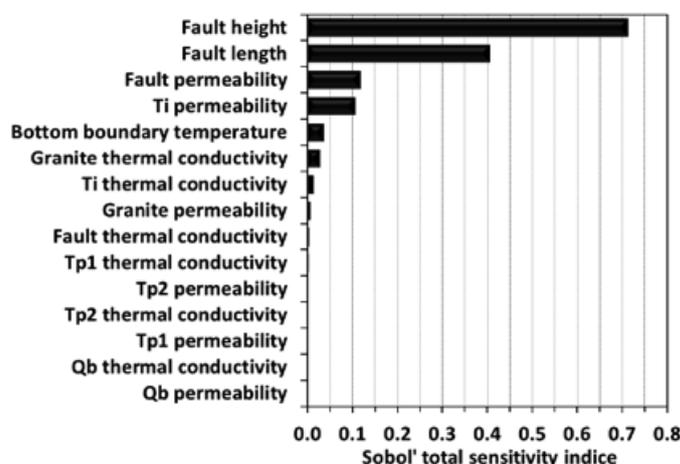


Figure 8: Sensitivity analysis

### 3. CONCLUSIONS

We have developed a stochastic inversion algorithm and software that works well with temperature and resistivity or MT data. When tested on synthetic datasets, the inversion process recovered models that were similar to the original synthetic models along with error estimates. We have also begun testing real datasets. Sensitivity analysis and ‘surrogate’ reduced order models appear to be a good approach to reducing computational effort. The flexibility of the approach allows the potential inclusion of other data

types such as geochemical signatures and geostatistical-based models of geologic structure. We envision the potential use of the algorithm as a method to generate alternative models and corresponding likelihoods to estimate uncertainties associated with a prospect and its role as a potential production location. The initial mesh and model generation has been developed to be compatible with commercially available geological modeling packages.

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