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Sensitivity of Temperature Predictions in Basin-Scale Hydrothermal Models

Noah D. Athens and Jef Caers

Department of Geological Sciences, Stanford University, Stanford, CA 94305

nathens@stanford.edu

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ABSTRACT

In extensional geothermal systems such as those in the Basin and Range Province, fluid-bearing fracture zones are known to be associated with structural complexity based on the locations of thermal springs. However, characterizing geothermal resource potential and reducing exploration risk, particularly in systems where there are no surface manifestations of the hydrothermal system, remains challenging. In this paper, we examine the relative impact of numerical model parameters on temperature predictions of regional-scale hydrothermal systems using coupled fluid and heat transfer modeling. The numerical model is composed of three primary domains: (1) crystalline basement rock, (2) sedimentary basin, and (3) range-bounding fault zone. Parameters in the Monte Carlo simulation include material properties, model geometry parameters, and boundary conditions. Using Monte Carlo simulation, 800 models were generated and solved while varying the above parameters, resulting in a broad range of model responses. Distance-based sensitivity analysis is used to assess the relative importance of model parameters in order to gain insight into the factors that drive thermal upwelling in regional hydrothermal systems.

1. INTRODUCTION

Despite decades-long interest in geothermal energy systems, the formidable risk of drilling multimillion dollar unsuccessful wells continues to hinder development of these resources. Because direct observation of geothermal reservoirs through drilling is severely limited, characterization of resources often depends on indirect observations through geophysical, geological, and geochemical investigations, providing an imperfect window into the subsurface. Therefore, the challenge is to develop a framework for integrating imperfect information into a quantitative model that can be used to predict geothermal features of interest while accounting for uncertainty in the underlying data and model.

In terms of physical data science, numerical modeling is the primary tool available for connecting observations about the subsurface to a prediction of a physical variable such as temperature. However, before one can build a numerical model, it is first necessary to decide what to include in the numerical model. This process is non-trivial, involving decisions about the modeling domain, boundary conditions, and material properties for each lithology in the model, as well as the degree of complexity of the model. Furthermore, if one considers the uncertainty of each model parameter, including, for example, uncertainty about the presence of structures or how to quantify heterogeneity and anisotropy of material parameters, then the process becomes outright impractical. To simplify the problem, we examine how Monte Carlo simulation and sensitivity analysis can be used to rank model parameters in order of relative impact on the model response with the aim of understanding which parameters are most important for predicting the occurrence of geothermal resources.

To demonstrate the utility of sensitivity analysis, we developed a parameterized two-dimensional, fully coupled heat transfer and groundwater model based on Dixie Valley, Nevada. Monte Carlo simulation was used to generate a dataset of 800 temperature profiles using model parameters randomly drawn from a prior distribution. Principal Component Analysis was used to transform the model responses to a lower dimensional space where responses were grouped together into classes based on Euclidean distance using k-means clustering. Finally, sensitivity of each model parameter was computed by comparing the cumulative distribution functions (CDFs) of each class to the original (prior) distribution.

2. MODELING APPROACH

To generate simulated temperature profiles for sensitivity analysis, we developed a numerical model to represent the regional hydrothermal system in Dixie Valley, Nevada and other similar Basin and Range style geothermal systems. In the Basin and Range Province, conventional hydrothermal geothermal systems are associated with Quaternary normal faults and circulation of fluids to depths in excess of 5 km (Person et al., 2008). The Basin and Range Province is a highly extended terrane, typified by north-to northeast-trending high angle block faulting that define grabens filled by Cenozoic sedimentary and volcanic deposits (Parsons, 1995). Despite syn-extensional magmatism that contributes to the region's high heat flow, geothermal systems in the Basin and Range are considered mostly non-magmatic in origin (Kennedy et al., 2000). Reservoirs are usually low to mid temperature (<200 °C) (Faulds et al., 2011), although temperatures up to 280 °C have been found at 3 km depth (Blackwell et al., 2000).

While previous hydrothermal modeling studies have separately examined the influence of basement rock permeability (Wisian and Blackwell, 2004), high-relief mountainous terrain (Forster and Smith, 1989), and heterogeneous permeability (Lopez and Smith, 1995), we have developed a single numerical model to examine these features and others jointly.

2.1 Numerical Model

The numerical model was developed using COMSOL Multiphysics Software. COMSOL Multiphysics is a finite element modeling package capable of solving fully coupled multiphysics problems. The equations used to solve for heat transfer and variable-density groundwater flow are standard, and the reader is referred to the COMSOL Reference Manual.

The two-dimensional basin-scale hydrothermal model (Figure 1) is composed of three domains: (1) crystalline basement rock, (2) sedimentary basin, and (3) range-bounding fault zone. The range-bounding fault zone is defined using COMSOL's fracture flow interface, a special application in which the equations for groundwater and heat transfer are solved in 1D and coupled to the surrounding mesh elements. As such, the narrow fault zone is not explicitly meshed in the model (Figure 1b).

A constant temperature of 20 °C and 1 Atmosphere pressure is specified at the top of the modeling domain, which represents the top of the water table. Recognizing symmetry at the sides of the modeling domain, the sides and bottom of the model are specified no flux conditions except for a heat flux boundary condition at the bottom of the model. Initial conditions establish a geothermal gradient of 40 °C/km and hydrostatic pressure. Simulations are run for 1 million years, effectively reaching steady state conditions.

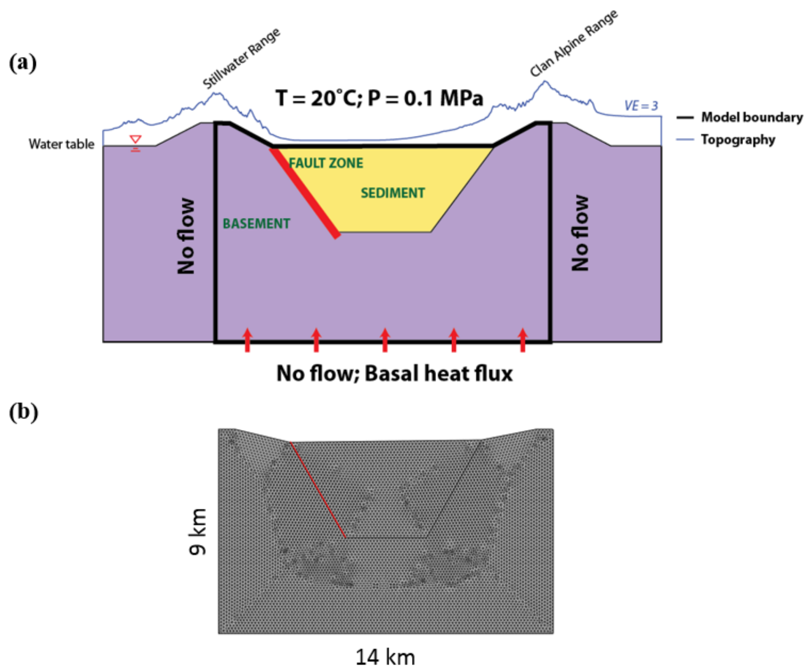

Figure 1: The top illustration (a) shows the conceptual model for the basin-scale hydrothermal model. The bottom illustration (b) displays an example of the finite element mesh on which solutions are calculated (approximately ~15,000 triangular elements).

2.2 Monte Carlo Simulation

Monte Carlo simulation was used to generate 800 COMSOL input models with model parameters randomly drawn from specified uniform distributions (Table 1). For the Monte Carlo study, 14 parameters were selected to be varied, relating to the boundary conditions, the geometry, and material properties of the model. The uniform distribution for each model parameter is intended to span the range of reasonable possible values for a Basin and Range geothermal system. Model parameters that are not included in the Monte Carlo study, such as porosity and density, were fixed to a constant value in all simulations and therefore do not significantly affect the sensitivity analysis.

Permeability fields for the basin and basement domains were separately generated using Sequential Gaussian Simulation implemented in the Stanford Geostatistical Modeling Software (SGeMS) (Remy et al., 2009). For each simulated permeability field, an exponential variogram model was used to create the "texture" of the permeability field (Figure 2). Three parameters in the Monte Carlo study (Table 1) are used to define the variogram model; the *range* adjusts the distance that correlation exists in the simulated permeability field, and the *mean* and *standard deviation* define a target normal distribution that scales the values of the simulated permeability field. Anisotropy was fixed in each simulation such that the distance of correlation in the horizontal direction is ten times greater than in the vertical direction. Finally, a log-linear trend was imposed on the permeability field such that permeability decreases by 3 orders of magnitude over 10 km depth (Achtziger-Zupančič et al., 2017).

Table 1: Monte Carlo Simulation parameters used to generate 800 input models.

Parameter	Distribution	Units	Explanation
Basal.Heat.Flux	U(0.06, 0.12)	W/m^2	Boundary condition
Basin.Depth	U(3, 5)	km	Geometry
Water.Table.Height	U(0.1, 1)	km	Geometry
Fault.Dip	U(50, 70)	degrees	Geometry
Basin.Asymmetry	U(0, 0.1)	km	Geometry
Fault.Width	U(0.01, 0.2)	km	Geometry
Thermal.Cond.Basin	U(1.5, 2.5)	W/(m*K)	Materials
Thermal.Cond.Basement	U(2, 3)	W/(m*K)	Materials
Permeability.Mean.Basin	U(-17, -14)	$\log_{10}$(m^2)	Materials
Permeability.STD.Basin	U(0.1, 1.5)	$\log_{10}$(m^2)	Materials
Permeability.Range.Basin	U(0.5, 5)	km	Materials
Permeability.Mean.Basement	U(-19, -16)	$\log_{10}$(m^2)	Materials
Permeability.STD.Basement	U(0.1, 1.5)	$\log_{10}$(m^2)	Materials
Permeability.Range.Basement	U(0.1, 2)	km	Materials

Figure 2 illustrates example COMSOL input models generated by Monte Carlo simulation. Because the geometry of each model is different, a unique finite element mesh is generated for each model. The element size is extremely fine (Figure 1b) in order to represent heterogeneous permeability fields. In contrast to the permeability field, thermal conductivity values are scalar values applied to the basement and basin domains respectively.

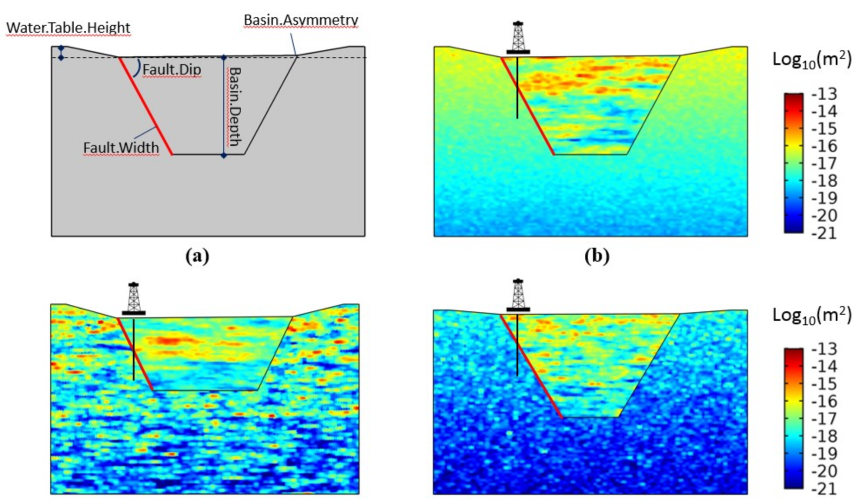

Figure 2: (a) Illustration of Monte Carlo parameters related to the geometry of the input model. (b, c, and d) Example model realizations. Colors show the permeability field. Well symbol indicates location of temperature-depth profiles.

2.3 Simulation Results

Temperature and Darcy Velocity fields were aggregated from 800 solved models. Because the boundary condition for the water table in the numerical model was specified as constant temperature and pressure, there is no constraint on the rate of recharge into the model during the simulation. Therefore, to avoid including unrealistic model solutions, we removed model solutions in which the recharge rate exceeded a generous threshold of 10 cm/year, which is 1.5 times greater than the infiltration rate assumed in Forster and Smith, 1989. In total, 208 models were removed, resulting in a dataset of 592 valid models for our analysis.

Temperature profiles to a depth of 3 km were extracted from a location 3.75 km from the left side of the model domain (Figure 2). The location and depth were chosen to represent a likely target of interest for geothermal development in a fault-controlled system. The majority of temperature profiles (Figure 3A) are approximately linear, with temperatures reaching 100 - 200 °C at 3 km depth.

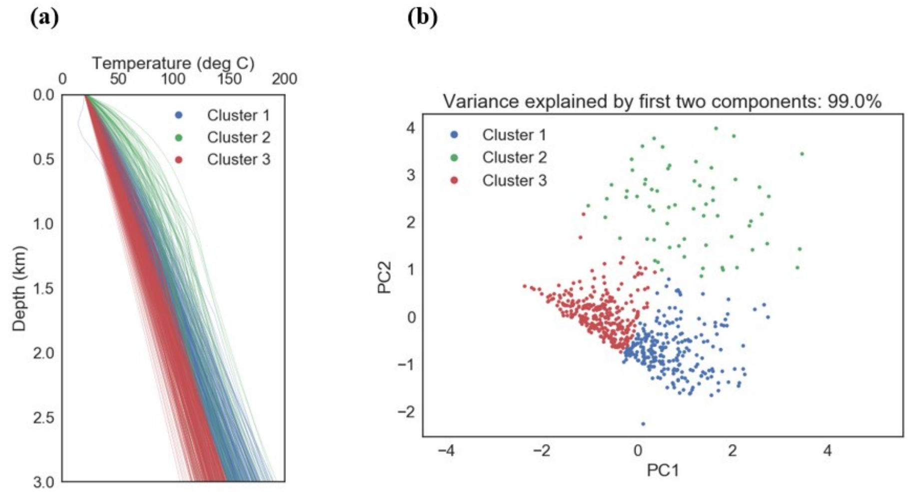

Figure 3: Temperature-Depth profiles from 592 models. Figure 2 shows the location of profiles. (a) Classified temperature-depth profiles. Colors represent classes determined by k-means clustering. (b) K-means clustering was applied to first two principal components of temperature-depth profiles.

3. SENSITIVITY ANALYSIS

The purpose of sensitivity analysis is to understand the relationship between a model response and model parameters. In this example, we illustrate the utility of an approach called Distance-based Generalized Sensitivity Analysis (DGSA) (Park et al., 2016). Model responses are separated into different classes, and then, for each parameter, the cumulative distribution functions (CDFs) for each class is compared with the original (prior) CDF. If the classified CDFs differ from the original CDF, then the parameter is deemed *sensitive*, meaning that the model response is affected by the value of the parameter.

3.1 Calculating Sensitivities

There are many different ways that the model responses (temperature profiles) can be separated into classes; the choice of method largely depends on the research question of interest. In this example, temperature profiles are transformed into a Euclidean space using Principal Component Analysis (Figure 3b), a linear algebra method for finding orthogonal bases that maximize variance in the data. Then, in this lower dimensional representation of the temperature profiles, the profiles were separated into three classes (clusters) using K-means clustering, a standard statistical learning algorithm for unsupervised classification. Figure 3a illustrates the three distance-based clusters in the original high-dimensional space of the temperature profiles. It can be observed that profiles in clusters 1 and 3 are distinguished by temperature gradient but otherwise are similarly linear. In contrast, profiles in cluster 2 are distinguished by relatively warm temperatures at shallow depth. The sensitivity analysis that follows will give insight into the parameters that control these features.

Figure 4a shows four CDFs of the “Basal.Flux” model parameter. The CDF of the prior (original) distribution is linear because values of Basal.Flux were drawn from a uniform distribution in the Monte Carlo simulation. However, CDFs computed on each set of clustered data are different, indicating that the model responses are *sensitive* to the Basal.Flux parameter. In contrast, model responses are *insensitive* to the Basin.Asymmetry parameter because all the CDFs are equivalent to the original (prior) distribution (Figure 4b).

The CDF analysis for each parameter is summarized in a Pareto plot (Figure 5) in which the parameters are ordered from most sensitive (at the top) to least sensitive (at the bottom).

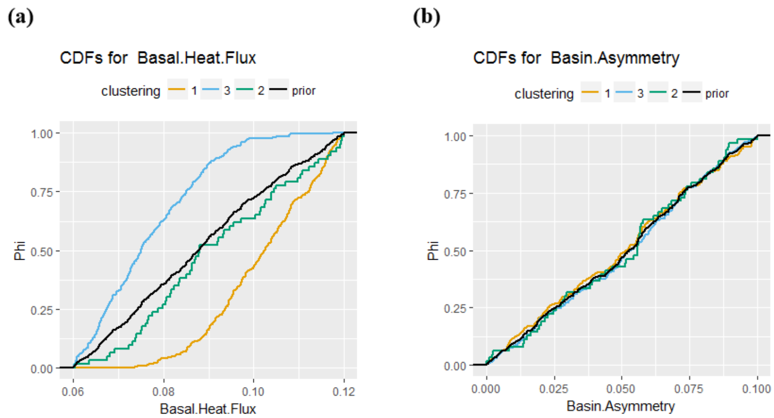

Figure 4: Cumulative Distribution Functions (CDFs) for two parameters from Monte Carlo simulation (Table 1). (a) Basal.Flux is determined to be a *sensitive* parameter because the CDFs of the clustered data distributions differ from the CDF of the prior (original) distribution. (b) Basin.Asymmetry is determined to be an *insensitive* parameters because there is no difference in the CDFs.

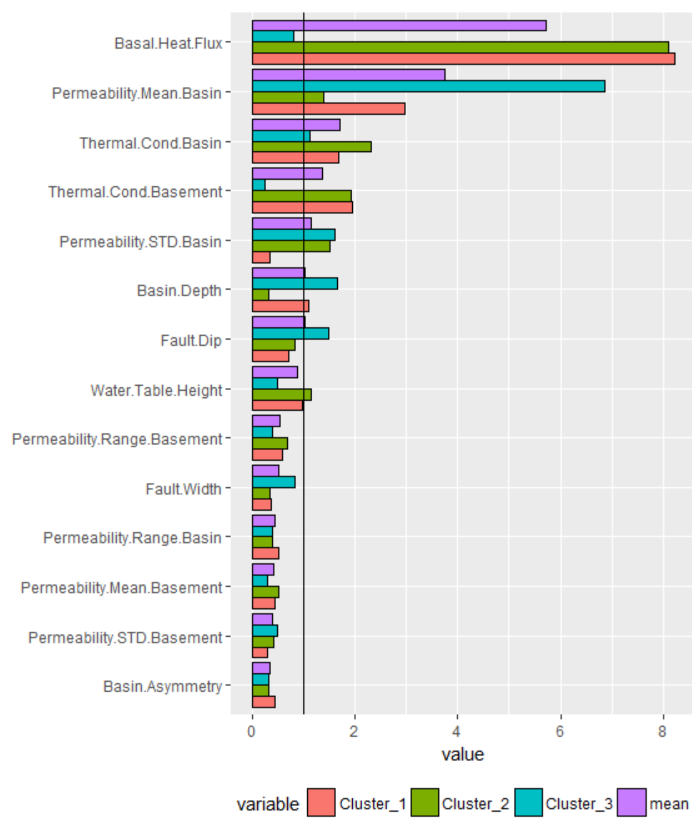

Figure 5: Ranked sensitivities displayed in a Pareto plot.

3.2 Interpreting Sensitivities

Based on the heat flow equation alone, it is expected that basal heat flux and thermal conductivity are important parameters for controlling conductive heat flow. Furthermore, it is also expected that permeability is an important parameter for controlling convective heat flow. Indeed, the sensitivity analysis confirms these parameters to be the most important for controlling the temperature profiles. However, there are several parameters that require additional inspection.

Many studies have suggested that topographically-driven flow is important for increasing advection in hydrothermal basins (Forster and Smith, 1989; Wisian and Blackwell, 2004). However, in the sensitivity analysis, the parameter "Water.Table.Height," which controls topographically-driven flow in the model, was determined to be *insensitive*. The reason for this is two-fold: (1) in the numerical model, basement permeability decreases with depth, thereby severely limiting fluid flow at depth, and (2) models that had unreasonably high recharge rates were removed from the analysis. In both cases, the majority of models have little fluid flow through the basement domain, and therefore basement-related parameters are relatively insensitive.

The width of the fault zone is also determined to be *insensitive* for a similar reason. Because of the lack of advection at depth in the basement rock, the fault zone did not contribute significantly to thermal upwelling. The only place where significant convection occurred was in the basin, which was controlled by the permeability of the basin. Interestingly, the parameter "Permeability.Range.Basin" is *insensitive* despite being a permeability-related basin parameter. Because anisotropy was fixed such that correlation of permeability values is 10 times greater in the horizontal direction than in the vertical direction, the *range* is primarily related to fluid flow in the horizontal direction, resulting in little impact on thermal fluid upwelling or cold fluid downwelling.

4. CONCLUSIONS

This work demonstrates that sensitivity analysis is a convenient tool for analyzing the relative importance of numerical model parameters on the model response. In the example presented, we showed that there were both *sensitive* and *insensitive* parameters in the numerical model, suggesting that the complexity of the numerical model could be substantially reduced without losing any information. Future work will expand the analysis presented here to include predictions of temperature conditioned on shallow temperature well data.

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