EVALUATING THE ROLE OF THE RHYOLITE RIDGE FAULT SYSTEM IN THE DESERT PEAK GEOThERMAL FIELD WITH ROBUST SENSITIVITY TESTING THROUGH BOUNDARY ELEMENT MODELING AND LIKELIHOOD ANALYSIS

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ABSTRACT

Large faults provide critical conduits that host deep fluid circulation supporting an economic geothermal reservoir by forming and maintaining fracture networks in response to local stress changes resulting from their slip. These networks provide the majority of connected porosity constituting the geothermal reservoir. However, these structures are generally geometrically complex and key attributes of such fault and fracture networks are often poorly constrained. To address the uncertainty that results from these limitations, we model slip on the geometrically complex Rhyolite Ridge normal fault system and the resulting local stress concentrations in the Desert Peak Geothermal Field in Nevada using the boundary element method (BEM) implemented in Poly3D.

We systematically explore and quantify the impact of uncertainty in the geometry of the Rhyolite Ridge fault system at depth and the tectonic stresses driving the slip on the predictions of fracture formation and slip in the surrounding volume due to local changes in stress. The affect of uncertainty in the input parameters to the model was evaluated through a sensitivity study in which: (1) models were run over a range of values for key input parameters such as fault height, dip, and the remote stress state; (2) the frequency distribution of predicted local stress states at an observation point in the reservoir was calculated; (3) the frequency distribution of model predictions was weighted by the probability distribution functions of the corresponding input parameter derived from field, laboratory measurements, or theoretical constraints.

This analysis reveals that the complex geometry of the fault system leads to a high degree of variability in the locations experiencing stress states that promote fracture, but that such locations generally correlate with the main injection and production wells at Desert Peak. The spatial distribution of the model results are validated against recently induced seismicity at Desert Peak, and the resulting smaller displacement and slip tendency on the fault surface are compared to tracer tests that infer flow-paths between injection and production wells to show how clamped faults can inhibit flow at depth, while providing a lateral flow boundary for the reservoir.

INTRODUCTION

Faults and fracture systems are known to significantly affect fluid flow by either acting as highly permeable conduits or as impediments to flow (e.g. review in Long et al., 1996). In hydrothermal systems, faults can cause fractures that create vertically extensive pathways capable of delivering heat from depth to the near surface through advective heat transport (Caine et al., 1996; Curewitz and Karson, 1997; Heffer, 2002). The sites of hydrothermal upwelling are localized along limited portions of fault traces, such as fault bends and terminations (tips), or in regions of fault intersection or overlap (Curewitz and Karson, 1997; Hickman et al., 1998; Bourne et al., 2000; Faulds et al., 2005; Eichhubl et al., 2009). Virtually all fault systems contain such geometric complexities, however only a small fraction of fault systems and geometric complexities act as fluid flow conduits sustained over geological periods of time from tens to hundreds of thousands of years. The premise underlying this
association is that slip on faults relaxes the shear stress on the fault surface and transfers the corresponding force into the surrounding volume resulting in local variation in the principal stress magnitudes and directions, enhancing deformation or potentially causing a change in the deformation mechanism (Bourne & Willemse, 2001; Davatzes et al., 2005), which is capable of maintaining permeability in chemically reactive geothermal environments. The dimensions of the volume affected scales with the size of the structures (and their geometric complexities) accommodating slip in the brittle-elastic shallow crust, and accounts for heterogeneity in permeability distribution. In short, the local stress state caused by faults depends on a variety of parameters, such as remote (i.e., regional) stresses driving slip, fault geometry, the attitude and distribution of established fracture populations around the fault, mechanical properties of the surrounding lithology, and the distribution of slip (Lockner & Beeler, 2002).

More practically, in many cases geothermal systems in the Basin and Range tectonic province have no surface expression that reveals the resource or that can guide the development of reservoirs. Even in developed reservoirs, key information about the subsurface structure controlling heat/flow can be missing. Determining zones ideal for geothermal production can thus be difficult in the absence of hot springs at the surface, or thermal anomalies either evident at the surface (e.g., Coolbaugh et al., 2007) or from existing boreholes. In the Basin and Range, many hydrothermal systems are controlled by the active, extensional normal faults characteristic of the region that provide the vertically extensive conduits necessary to bring hot water to shallow depth by groundwater circulation (e.g., Barton et al., 1998; Hickman et al., 1998). Therefore, modeling the stress distribution around faults in an extensional tectonic setting, such as the Basin and Range, can provide a useful tool that aids in geothermal exploration.

However, there is often significant uncertainty associated with the key parameters of fault systems required to create a mechanical stress model around faults. Even in developed geothermal systems, data regarding the subsurface is often either highly lacking or absent, making model parameter selection difficult or impossible. This also means that competing conceptual reservoir models cannot be tested effectively. In the case of a fault system that has been mapped in detail at or near the surface that is associated with an existing or potential geothermal reservoir, limited data can still be utilized to constrain the fault model through rigorous parameter sensitivity analysis. Statistical analysis of both the resulting output distribution from parameter sensitivity studies, as well as the existing data that can be used to constrain modeling parameters, can jointly be used to make parameter selections in order to construct a fault model useful in geothermal exploration.

The Desert Peak Geothermal Field, NV, located in the Basin and Range is one example of a hydrothermal area associated with a bend or step in the Rhyolite Ridge normal fault system that has been mapped in detail at the surface (Figure 1) (Faulds et al., 2010). Enhanced Geothermal System (EGS) well DP 27-15 is located along the northernmost fault trace with active injecting and producing wells located within ~0.5 to ~2 km to the SW within an extensional step or bend between two major NE-SW striking normal faults (Figure 1). Although this spatial association is clear, several problems remain: (1) The fault is comprised of several distinct segments, making it uncertain whether all, some, or none are actively slipping; (2) Stress transfer among segments can produce spatially varying patterns of slip direction on the fault segments and deformation in the surrounding volume; (3) All of the key parameters including the fault geometry, mechanical properties of the rock, and the stress state have associated uncertainties, especially at depth.

We investigate the structural control of the Rhyolite Ridge fault system on fracture potential, i.e., the conditions promoting fracture formation and slip at Desert Peak through boundary element modeling (BEM) of slip on the Rhyolite Ridge fault system and resulting deformation in the adjacent rock volume. A heuristic modeling approach is adopted to investigate the sensitivity of this elastic deformation to details of fault geometry and stress state within uncertainties derived from mapping and borehole studies as well as reasonable constraints on the state of stress in the surrounding crustal volume from the frictional strength of rock. Variation in the outcomes of these models can be quantified by exploring these uncertainties, thus revealing which results are poorly constrained due to the uncertainty of input model parameters and which outcomes are robust and have a high probability of occurrence. We show that this approach provides a practical tool for geothermal exploration and development by (1) determining which geologic models are both compatible with field observations and quantifying the model probability in light of known uncertainties and (2) identifying the types of data and locations that would be most useful to refine or test a geologic model.

**GEOLOGIC setting**

The Desert Peak Geothermal Field is located in the Basin and Range Tectonic Province along the
N-NE striking Rhyolite Ridge normal fault system. The fault system is characterized by two large overlapping faults with multiple fault segments within the relay zone containing abundant bends and intersections near the production wells (Figure 1). The hydrothermal system itself has no active surface expression that would indicate the presence of a geothermal reservoir (Benoit et al., 2006; Kratt et al., 2006; Faulds and Garside, 2003).

The conceptual fault model for Rhyolite Ridge is that the two major N-NE striking faults have formed an active left-stepping overlapping relay that has been breached through fault tip propagation and truncating intersections (Faulds and Garside, 2010, thus hard-linking the relay. Slip on these segments could cause stress concentrations that increase fracture density. The characteristics of the system are derived from surface fault maps (e.g., Faulds and Garside, 2003; Faulds pers comm. November, 2011), geological characterization of well data (Lutz et al., 2009), geomechanical analysis of well data (Robertson-Tait et al., 2004; Davatzes and Hickman, 2009; Hickman and Davatzes, 2010), and rock mechanical analysis of representative core (Lutz et al., 2010). Additional constraints on the behavior of the reservoir are derived from pressure interference tests (Zemach et al., 2010), tracer studies (Rose et al., 2010), and local seismic monitoring (see Nathwani et al., 2011).

METHODOLOGY

The numerical modeling method employed is the linear elastic boundary element method (Crouch and Starfield, 1983) implemented in the Poly3D (Thomas, 1992) modeling software. In Poly3D, the fault surfaces are discretized into triangular elements modeled as displacement discontinuities within a continuous isotropic homogeneous linear elastic half or whole space rather than discretizing the entire three-dimensional rock volume, resulting in much more efficient computation. Poly 3D has been used extensively to model multiple faults that interact structurally that have a similar arrangement as the faults mapped at Desert Peak (Crider and Pollard, 1998). Temperature, fluid flow, or chemical effects are not modeled. Displacement discontinuity or traction boundary conditions are specified on the elements and a uniform far field strain or stress tensor is applied to induce deformation. A quasi-static solution of stress and strain is calculated at observation points in the surrounding volume using linear elastic properties (Figure 2). The elements comprising the faults were constrained to have zero residual shear tractions and zero normal displacement – effectively simulating a complete shear stress drop, or a frictionless surface, without opening or interpenetration of the modeled surfaces. The impact of friction has been evaluated but not presented here. Generally, modeled fault friction causes faults to have less displacement, and therefore cause less local stress concentrations, but some complexity in the model solution can occur that is as straightforward. Moreover, further complexity in local stresses can arrive when a friction solver accounts for fault models that allow for opening, causing greater stress concentrations at point contacts along faults (as discussed in Kaven et al., 2012, and Swyer, 2013). The element edge length used was selected to avoid singularity effects at the well locations caused by the numerical method that extend the length of one element into the surrounding volume, as well as to minimize computation time. The uniform remote stress tensor is consistent with
the approximate reservoir depth of 930 m based on a stress model of well DP 27-15, which has been logged to determine the direction and magnitude of the least compressive horizontal stress, $S_{\text{hmin}}$ (Davatzes and Hickman, 2009; Hickman and Davatzes, 2010). Model calibration is achieved by comparing the model results to observation points placed coinciding with well DP 27-15 (Figure 2). The elastic constants of Young’s Modulus and Poisson’s Ratio used in the models and the frictional strength used to better constrain stress were obtained from mechanical testing of core samples from wells at Desert Peak (Lutz et al., 2010) (Table 1).

For simplicity, the initial model fault was taken as a rectangular flat plane representative of the northernmost fault trace of Rhyolite Ridge and assigned a dip of 60°, typical for normal faults (Figure 2). The stress tensor initially used is derived from the magnitude and direction of $S_{\text{hmin}}$ observed in well DP 27-15, the vertical stress, or $S_v$, from the weight of the overlying rock, and the most compressive horizontal stress, or $S_{\text{Hmax}}$, assumed to be the average of the other two principal stresses (Figure 2) as described by Hickman and Davatzes (2010) (Table 1), and the pore pressure, or $P_p$, used was taken as hydrostatic pressure from the depth to the water table.

Efficient BEM simulation facilitates analysis of the sensitivity of fault slip and related local stresses to a reasonable range of input model parameters. Systematic forward models are used to interrogate the relationship between the local stresses and poorly constrained aspects of the fault geometry such as the vertical extent of the fault and its dip, the active fault trace, and the remote stress boundary conditions. The resulting family of forward models reveals trade-offs between these coupled parameters. As a straightforward measure of sensitivity, this family of models also characterizes the frequency distribution of model predictions (outcomes) of the local stress state resulting from the range of the corresponding input parameters, and reveals the most common outcomes. This frequency distribution derived from the forward modeling is further weighted by the uncertainties of the input parameters or by additional external constraints to describe the most likely result in the family of models.

To better understand the statistical significance of changing input parameters on a stress model, an analysis of model likelihood was performed by finding the most commonly occurring output values from the batch of models. Model outputs from the two-parameter space were compiled as histograms to describe the frequency distribution of model predictions. The histogram in Figure 3a summarizes the variability in the predicted magnitude of $S_{\text{hmin}}$ including the most common predictions, the spread of the distribution, and its shape (i.e., unimodal, bimodal, skewed). In addition, the

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**Table 1: Model Parameters (individual models differ as stated)**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Magnitude</th>
<th>Uncertainty</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Geometry</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Approx. element length</td>
<td>150</td>
<td>-</td>
<td>m</td>
</tr>
<tr>
<td>Fault dip</td>
<td>60</td>
<td>± 15</td>
<td>degrees</td>
</tr>
<tr>
<td>Depth to lower fault tip</td>
<td>2000</td>
<td>-</td>
<td>m</td>
</tr>
<tr>
<td><strong>Stress Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depth(DP27-15)**</td>
<td>930</td>
<td>± 12.5</td>
<td>m</td>
</tr>
<tr>
<td>$S_v$</td>
<td>22.6</td>
<td>± 0.7</td>
<td>MPa</td>
</tr>
<tr>
<td>$S_{\text{hmin}}$</td>
<td>13.8</td>
<td>± 0.4</td>
<td>MPa</td>
</tr>
<tr>
<td>$S_{\text{Hmax}}$</td>
<td>18.2</td>
<td>± 0.6</td>
<td>MPa</td>
</tr>
<tr>
<td>$P_p$</td>
<td>8.0</td>
<td>± 0.6</td>
<td>MPa</td>
</tr>
<tr>
<td>$S_{\text{hmin}}$ Azimuth</td>
<td>114</td>
<td>± 17</td>
<td>azimuth</td>
</tr>
</tbody>
</table>

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**Rock Properties**

- Young’s Modulus, E: 34.2 ± 11.0 GPa
- Poisson’s Ratio, v: 0.18 ± 0.07 unitless
- Laboratory Friction: 0.77 ± 0.12 unitless

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**Elastic Properties**

histogram is presented as a stack so that contributions from different fault dip ranges to the distribution of \(S_{\text{hmin}}\) magnitudes is retained. Although the results in Figure 3a summarize the sensitivity of a model prediction, such as \(S_{\text{hmin}}\) to fault height and dip, these results do not necessarily predict the most likely input parameters. To identify the most likely parameter combination, the probability of the fault height and dip must be evaluated. This probability distribution is illustrated in Figure 3b and defines a function that ranges from zero, corresponding to values that are not permissible, to one which corresponds to the highest probability. This distribution defines a weighting function in terms of a mean and standard deviation within a bound range. Such a weighting function can be obtained from statistical analysis of field data or alternatively from external data constraints considering the likely range of the input parameter. Once defined, this weighting function (Figure 3b) is applied to the frequency distribution of \(S_{\text{hmin}}\), that then describes the most probable magnitudes (Figure 3c).

This simple weighting scheme is adequate for adjusting predictions derived from a single input parameter. However, in the two-parameter space of fault height and dip, two weighting functions should be considered to constrain a fault model. Averaging the counts for the two resulting data distributions causes a redundancy in the input parameters of fault height and dip because they are both factors in creating the two data distributions that are being averaged, causing them to be considered twice for the final distribution. When considering the constraints on each input parameter only once by weighting the distribution by each function one after the other, a discrepancy is created by two different final data distributions that depend on the order in which the weighting functions were applied. Instead, the two weighting functions were used to factor the data distribution simultaneously. This is done by creating a new function of the model output parameter, in this case \(S_{\text{hmin}}\), that is the summation of the two input weighting functions for fault heights and dips that generate model outputs within each histogram bracket. This produces a new weighting function that is applied to the total counts on the histogram regardless of which input parameter contributed to the data distribution (Figure 4c). The mean of the new data distribution is considered the most likely \(S_{\text{hmin}}\) and was used as criteria for selecting height and dip for the fault model, while its standard deviation was used to assess the confidence of the model prediction. The model likelihood of height and dip is based on the height/dip combination that creates \(S_{\text{hmin}}\) that is the most similar to the model predicted \(S_{\text{hmin}}\).

Figure 3: Example of process for weighting the model output using a function of an input parameter. The frequency distribution (a) of the model prediction as a stacked histogram of results from various fault dips, which are then (b) are weighted by a function of the input parameter \((x_i)\), fault dip, from an independent constraint \((x_{IC})\) with its standard deviation \((x_{SD})\), or in this case, as a normal distribution representing the mean and standard deviation of the pre-existing data to create (c) a new weighted frequency distribution.
The results of $h$ of 930. The examples of using both weighting functions, and $h_{\text{min rem}}$ (Jaeger and Cook, 1979; fault hole data, the fault geometry was tested particular to the stress regimes. (3) The fault geometry of mapped fault segments two major large scale faults. The most productive wells at Desert Peak are then used on constraints on $a$) fault dip and $b$) fault height are summed together for each combination of the two parameters to create $c$) the new data distribution. The mean value is considered the preferred model output, and the standard deviation and data distribution are a proxy for uncertainty. The input parameters that create model outputs closest to the preferred output are selected to construct the stress model.

Once the model parameters have been selected from the sensitivity studies, they are applied to a fault model that includes the mapped fault trace at the surface in order to better understand how the details of fault overlap, curvature, and intersection cause local stress concentrations by contouring them in an observation plane at the reservoir depth of 930 m. The most productive wells at Desert Peak are then mapped on the contours to observe whether or not they correlate to locations of concentrated stress consistent with an increased tendency for fault slip, and to validate that this method can be used for geothermal exploration.

**RESULTS**

Modeling of the fault system at Desert Peak was conducted through various sensitivity studies of fault geometry and far-field stress state. (1) In the first series of models, the fault geometry was tested by varying fault dip and in-plane length from the surface to the lower tip of the fault along a flat planar rectangular fault (depth). (2) The remote stress tensor was varied by allowing a range from normal faulting to strike slip stress regimes. (3) The fault step along the Rhyolite Ridge system was modeled as three continuous faults that bend in order to hard-link two major large scale faults that reproduces the geometry of mapped fault segments (Figure 1).

**(1) Simple Geometry Sensitivity Study**

The dip angle and depth to the lower tip of the Rhyolite Ridge Fault systems are poorly constrained by outcrop (Faulds and Garside, 2003), seismic reflection (Zemach et al., 2009), earthquake (e.g., Nathwani et al., 2011), and borehole data (Faulds et al., 2003; Lutz et al., 2009). To constrain these geometric parameters, we model response to variations in fault dip and in-plane fault length perpendicular to strike (depth). The azimuth of the remote $S_{h_{\text{min}}}$ ($S_{h_{\text{min rem}}}$) was set perpendicular to the fault strike so that the fault orientation is reflective of remote stresses assumed to cause fault formation (Jaeger and Cook, 1979). The magnitude of $S_{h_{\text{min rem}}}$ was derived from a critically stressed friction failure criterion for normal faults (Jaeger and Cook, 1979; Zoback, 2007):

$$S_{h_{\text{min rem}}} = \frac{S_v - P_p}{\left(\mu^2 + 1\right)^{1/2}} + P_p$$  \hspace{1cm} Eq. 1

Where $\mu$ is the coefficient of friction, taken as 0.77 which is the value obtained from tri-axial compression testing of rock samples from Desert Peak (Lutz et al., 2010). Since the model includes a complete stress drop, these results represent the maximum stress perturbation. The resulting stress distribution is calculated at the stimulation depth in well DP 27-15 for the local least compressive horizontal stress ($S_{h_{\text{min loc}}}$), the vertical stress ($S_v$), the differential stress, and the mean stress. The results of all analyses are plotted as stacked frequency distributions in order to show which input parameters contribute to the most commonly occurring model outputs for each parameter (Figure 5).

The frequency distributions were then weighted with functions that favor the most likely geometric characteristics, expressed as probability distribution functions, for fault height and dip based on the mechanical properties of the rock for dip, and fault displacements taken from field maps and cross sections for height. The derivation of these functions was based on a simple normally distributed exponential function that considers the mean value and the standard deviations of existing data.

The weighting function for fault dip angle was based on the average internal friction angle ($\phi_i$), or the angle between the most likely shear failure plane and the greatest compressive principal stress, measured in triaxial experiments on cores from Desert Peak (Lutz et al., 2010). Since this property varies by stratigraphic unit, and the model is homogeneous, a weighted average calculated from the thickness of each lithotype at depth to obtain a representative value (Table 4). Since this region is dominated by normal faulting, the greatest
compressive principal stress is vertical as verified by Hickman and Davatzes (2010), which makes the preferred dipping angle $90^\circ - \phi_i$. The standard deviation was taken from the mean value and the population of values that represent the different lithotypes. Thus, the function used to weight the histograms based on fault dip is Eq. 2:

$$f(dip) = \exp \left( \frac{(dip - (90 - \phi_i))^2}{2 \sigma_d^2} \right)$$

Eq. 2

Table 2: Internal Friction Angle of Lithotypes at Desert Peak from Lutz et al. (2010)

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Depth</th>
<th>Internal Friction</th>
</tr>
</thead>
<tbody>
<tr>
<td>devitrified rhyolite</td>
<td>696.77</td>
<td>29.3</td>
</tr>
<tr>
<td>argillic rhyolite</td>
<td>724.21</td>
<td>35.4</td>
</tr>
<tr>
<td>argillic rhyolite</td>
<td>729.08</td>
<td>32.5</td>
</tr>
<tr>
<td>siliceous rhyolite</td>
<td>742.80</td>
<td>45.9</td>
</tr>
<tr>
<td>siliceous rhyolite</td>
<td>756.82</td>
<td>38.2</td>
</tr>
<tr>
<td>siliceous rhyolite</td>
<td>786.08</td>
<td>47.6</td>
</tr>
<tr>
<td>illitic/siliceous</td>
<td>789.74</td>
<td>44.4</td>
</tr>
<tr>
<td>illitic/siliceous</td>
<td>799.80</td>
<td>42.2</td>
</tr>
<tr>
<td>siliceous metamudstone</td>
<td>835.46</td>
<td>33.8</td>
</tr>
</tbody>
</table>

**Depth Weighted Friction Angle ($\phi_d$)**

| Standard Deviation ($\phi_d$) | 31.0 |

The fault height weighting function was based on an empirical relationship between fault slip and the length of a fault in the direction of slip. The accumulated geologic slip across the fault near well DP 27-15 was inferred from the offset of stratigraphic layers in the geologic map and cross-section of Desert Peak by Faulds (2010) assuming pure dip slip. The mean value and uncertainty range used in the weighting function was based on displacements between an older volcanic ash layer, and a more recent volcanic ash flow deposit. The discrepancy between these two offset layers causes uncertainty about what depth extent of the fault is actively slipping. Because the two layers are deposited at different times they show different slip magnitudes since the older layer would have been subject to more slip than the younger layer due to its earlier deposition. Since the lower portion of the fault may either have healed due to mineral precipitation or may no longer be as brittle due to the high geothermal gradient, it is conservative to assign a range of uncertainty tied to a maximum offset from the older ash deposit, and the younger volcanic flow. The fault displacements were then converted to fault heights based on an empirical relationship between the maximum or mean displacement, and the length of a fault in the direction of displacement (Eq. 3) (from Twiss and Moores, 2007, pg. 81):

$$f_h(\text{height}) = \frac{f_h(\text{height})f(dip)}{f_{mean}^2} s \pm \frac{b}{2}$$

Eq. 5

Where $\delta$ is fault displacement, $L_f$ is the length of a fault, and $p$ and $B$ are empirically derived constants so that $p$ represents the slope and $-\log B$ represents the $y$-intercept of the function. The overall trend for faults on the length-scale of Rhyolite Ridge is a slope of $p = 1.5$, and a $y$-intercept of $-\log B = 2.0$. The minimum fault displacement from the cross-section is ~63 m for the younger layer, which would cause a fault height of 3.4 km, and the maximum displacement is ~1625 m for the older layer, which would cause a fault height of 28.2 km. This gives a mean fault height value ($L_{fmean}$) of 15.8 km and a standard deviation ($L_{fSD}$) of ±12.4 km to be used in the weighting function. The function used to weight the histograms based on fault height is Eq. 4:

$$f_h(\text{height}) = \exp \left( \frac{(\text{height} - L_{fmean})^2}{2L_{fSD}^2} \right)$$

Eq. 4

Using these functions to weight the output parameters, new frequency distributions reflect how the additional data constraints of internal friction angle and fault displacement alter the most likely model prediction. The function used to weight the data with both functions simultaneously is Eq. 5:

$$f_h(m_y) = f_h(\text{height})f(dip)_{for m_y} S \pm \frac{b}{2}$$

Where $m_y$ is a modeling output parameter for a given fault dip, and height, combination, $S$ is the set of bin centers, and $b$ is the bin width. The new frequency distributions show a much more definitive model prediction, except for the azimuth of $S_{\text{min}}$, which shows a bimodal distribution (Figure 6). This is an indication that $S_{\text{min}}$ azimuth is a very sensitive and unstable model output. The mean values of the new frequency distributions are considered to be the model likelihood prediction.

In order to make a selection of fault height and dip to constrain the model, the differences between the five model outputs for all the runs in the sensitivity study and the model likelihood predicted values (Figure 6) are normalized for each model output, and then summed for each combination of height and dip. The normalization of all the model outputs inherently causes the most sensitive outputs to dominate the overall likelihood prediction. The height and dip combination that produces local stresses that are closest to the likelihood predicted values are used to constrain the fault model geometry (Figure 7). As a measure of uncertainty for this model prediction, the plot has a single contour at one standard deviation of the data in the two-parameter
space and for the model likelihood prediction. The likelihood prediction displays a bimodal distribution similar to the frequency distribution of the azimuth of $S_{\text{hmin}}$, due to the fact that it is the most sensitive output (Figure 6). The fault geometry that minimizes the normalized difference for the model likelihood predicted outputs has a height of 4.9 km and dips 69°, and was then used for all subsequent modeling.

Figure 5: Histograms of model predictions, stacked to show contributions from various fault heights shown on the top row and fault dips shown on the bottom row.

Figure 6: Histograms of model outputs weighted using both functions simultaneously. The stress plots show more definitive preferred values, except the azimuth of $S_{\text{hmin}}$, which has a bimodal distribution.

The white star indicates the preferred geometry where the normalized difference is the smallest. The white contour is placed at the standard deviation of the data populating the contoured plots.

(2) Stress Tensor Sensitivity Study

The same method was used to constrain the remote stress that drives fault slip by adjusting the magnitude of the remote minimum horizontal principal stress, $S_{\text{hmin}}^\text{rem}$, and the remote maximum principal horizontal stress, $S_{\text{Hmax}}^\text{rem}$, within stress polygons that define the permissible range of stress states that can be supported given the assumed presence of well oriented faults of a given frictional strength (Figure 8a) (See discussion in Zoback, 2007 and references therein). In this case, the polygons were derived from a friction coefficient of 1.0, which means that stress conditions within the polygon are stable whereas stress conditions outside the polygons cause slip that relieves differential stress. Thus, the edges of the polygon represent stress states in which fractures are critically stressed for shear failure, and stress states outside the polygon will not be achieved due to fault slip.

Values of $S_{\text{hmin}}^\text{rem}$ were derived from various friction coefficients consistent with Byerlee’s Law.
(Byerlee, 1978) using Equation 1 that includes 0.77, which is the average value from laboratory experiments on core samples from Desert Peak (Table 2) (Lutz et al., 2010), the upper and lower limits of the Byerlee friction range of 0.6 and 1.0 which is an empirically derived range of friction for crustal rocks (Byerlee, 1978), and 0.48 which is consistent with active slip of the magnitude of $S_{\text{hmin}}$ and $S_v$ in well DP 27-15 (Hickman and Davatzes, 2010) (Figure 8b). The value of $S_{\text{Hmax}}$ was adjusted for each $S_{\text{hmin}}$ magnitude within the normal and strike-slip fault stress regimes because there is no evidence supporting reverse faulting (Faulds and Garside, 2003; Hickman and Davatzes, 2010).

As with the parameters of fault geometry, the results of the two input parameters were weighted with functions that consider an additional constraint. The function used to constrain $S_{\text{hmin}}$ was based on stress magnitudes from the average sliding friction coefficient and the standard deviation from the population of laboratory measurements, weighted by the thickness of their representative lithotype at depth (Table 3). The mean value and the upper and lower uncertainty range of friction coefficient were used in Equation 1 to obtain a mean value of $S_{\text{hmin}}$ of 12.22 MPa and a standard deviation of 1.15 MPa. Therefore, the function used to weight the outputs based on $S_{\text{hmin}}$ is Eq. 6:

$$f_{\text{hmin}}(S_{\text{hmin}}) = \exp \left( \frac{(S_{\text{hmin}} - 12.22\,\text{MPa})^2}{2(1.15\,\text{MPa})^2} \right)$$

Eq. 6

### Table 3: Coefficients of friction for various litholotypes at Desert Peak from Lutz et al., 2010

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Depth (m)</th>
<th>Coefficient of Friction</th>
</tr>
</thead>
<tbody>
<tr>
<td>devitrified rhyolite</td>
<td>696.77</td>
<td>0.67</td>
</tr>
<tr>
<td>argillic rhyolite</td>
<td>724.21</td>
<td>0.70</td>
</tr>
<tr>
<td>argillic rhyolite</td>
<td>729.08</td>
<td>0.65</td>
</tr>
<tr>
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<tr>
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<td>786.08</td>
<td>0.96</td>
</tr>
<tr>
<td>siliceous metamudstone</td>
<td>835.46</td>
<td>0.66</td>
</tr>
</tbody>
</table>

| Depth Weighted Friction | 0.66   |
| Standard Deviation     | 0.16   |

We investigated the sensitivity of the borehole observation and deformation around the fault to uncertainty in the remote stress tensor by modeling remote stress states that systematically sampled the range from the observed stress state to the most extreme ranges of $S_{\text{hmin}}$ and $S_{\text{Hmax}}$ allowed by the frictional strength of the crust (e.g., Townend and Zoback, 2002), which is here taken to be a coefficient of 1.0 as a maximum value consistent with Byerlee friction (Byerlee, 1978). Thus $S_{\text{hmin}}$ at the depth of the mini-hydraulic fracture might vary from the observed magnitude of ~0.61 of $S_v$ to the frictional limit of ~0.46 of $S_v$ (Equation 1).

The four magnitudes of $S_{\text{hmin}}$ used were derived from various coefficients of friction using the critically stressed frictional failure criterion for normal faults described above (Equation 1). The $S_{\text{hmin}}$ magnitudes correspond to friction values of 0.48 which reproduces the stress state observed in the well (Hickman and Davatzes, 2010), 0.6 and 1.0 which represents the Byerlee friction range for a variety of brittle rocks (Byerlee, 1978), and 0.77 which is the average value obtained from triaxial compression testing of rock samples from Desert Peak (Lutz et al., 2010). The stress tensor was aligned perpendicular with the fault strike just as in the study of simple fault geometry described above. This configuration minimizes the potential influence of $S_{\text{Hmax}}$ on stress rotations, as $S_{\text{Hmax}}$ acts parallel to the flat-planar fault. In cases where $S_{\text{Hmax}}$ is not aligned with the strike of the fault we expect similar behavior but with slightly greater sensitivity to the effects of $S_{\text{Hmax}}$ magnitude. The resulting range of stress states define a polygon with axes of $S_{\text{hmin}}$ and $S_{\text{Hmax}}$ normalized to the remote vertical stress, whose outer limits are given by the highest friction coefficient, the principal stresses, and the fluid pressure. This approach allows a range of physically permissible stress states from the normal faulting to strike slip faulting stress regimes to be assessed.

The family of simulations that explore the range of $S_{\text{Hmax}}$ for each friction coefficient are weighted so that the values of $S_{\text{Hmax}}$ are forced to range between the remote vertical stress ($S_v$) and the average of $S_v$ and $S_{\text{hmin}}$. Since the range of $S_{\text{Hmax}}$ is different for each magnitude of $S_{\text{hmin}}$ (Figure 4.2.1b), there are four different functions that weight the model outputs that result from the friction coefficient used to derive $S_{\text{hmin}}$. Therefore the function is given in its general form:

$$S_{\text{Hmax mean}}(S_{\text{hmin}}) = \frac{S_v + S_{\text{hmin}}}{2}$$

Eq. 7

$$S_{\text{Hmax SD}}(S_{\text{hmin}}) = \frac{S_v + S_{\text{hmin}}}{2}$$

Eq. 8

$$f_{\text{SD}}(S_{\text{Hmax}}) = \exp \left( \frac{(S_{\text{Hmax}} - S_{\text{Hmax mean}})^2}{2(S_{\text{Hmax SD}})^2} \right)$$

Eq. 9
Figure 8: a) Stress polygons showing normal faulting (N.F.), strike-slip faulting (S.S.), and reverse faulting (R.F.) stress regimes for a friction coefficient equal to 1.0. b) Values of \( S_{h\text{min}}^{\text{rem}} \) used were derived from friction coefficients of 0.77 from rock mechanics testing of core samples at Desert Peak, 1.0 and 0.6 representing the Byerlee friction range, and 0.48 which is representative of the stress state observed in well DP 27-15 at Desert Peak. \( S_{H\text{max}}^{\text{rem}} \) is adjusted along vertical lines for each \( S_{h\text{min}}^{\text{rem}} \) value used within the normal and strike-slip stress regimes.

Where \( S_{H\text{max}}^{\text{mean}} \) and \( S_{H\text{max}}^{\text{SD}} \) are the mean and standard deviation respectively of the most compressive horizontal stress, and are both functions of \( S_{h\text{min}}^{\text{rem}} \). The mean value is in the center of the preferred \( S_{h\text{min}}^{\text{rem}} \) range and the standard deviation is half of this range. The new function that is applied to weight the frequency distribution of model output predictions that sums both functions together is:

\[
f_{S_{h\text{min}} S_{H\text{max}}} (m_y) = f_{S_{h\text{min}}} (S_{h\text{min}}^{\text{rem}}) f_{S_{H\text{max}}} (S_{H\text{max}}^{\text{rem}})\sum_{m_y} f_{S_{h\text{min}}} (S_{h\text{min}}^{\text{rem}}) f_{S_{H\text{max}}} (S_{H\text{max}}^{\text{rem}})
\]

where \( m_y \) is a modeling output parameter for a given combination of the greatest and least compressive remote horizontal stress, \( S \) is the set of bin centers, and \( b \) is the bin width.

After weighting the data, the resulting data distributions for the model outputs show clear preferred model outputs except for the local \( S_{h\text{min}}^{\text{rem}} \) magnitude, which has a bimodal distribution (Figure 4.2.3). However, the uncertainty range is much larger for these frequency distributions than the fault geometry study. The model that is best fit to the mean of all the model outputs, as well as the deterministic solution based on the well observation, is \( S_{h\text{min}}^{\text{rem}} \) of 11.5 MPa and \( S_{H\text{max}}^{\text{rem}} \) of 18.8 MPa, or a \( S_{H\text{max}}^{\text{rem}}/S_{h\text{min}}^{\text{rem}} \) ratio of ~0.83.

The model results are presented as contoured maps at the reservoir depth of 930 meters. Contours showing change in \( S_{h\text{min}} \) were used to assess the potential for tensile failure, where decrease corresponds to a superposed tension, and therefore increased fracture potential. In solid rock with pore space that contains a fluid, the pressure of that fluid will reduce the normal stress on a fracture or fault surface, and will also reduce the normal components and/or principal values of a stress tensor. Since \( S_{h\text{min}} \) is a principal stress, its magnitude is reduced by the pore pressure in the rock, representing the effective stress condition for tensile failure, also known as the effective stress. In cases where the effective \( S_{h\text{min}} \) is low enough, it predicts locations of tensile failure, where negative values represent tension meaning tensile failure will most likely occur due to the fact that brittle rocks are highly unstable under tension (Jaeger et al., 2007). Shear failure potential was assessed using the maximum Coulomb shear stress \( (S_c) \), which has also been used as a proxy for fracture density (as per Maerten et al., 2002; Childs et al., 1995).
Figure 9: Histograms weighted by functions for $S_{\text{hmin}}$ and $S_{\text{Hmax}}$. Most model outputs show a distinct preferred value except $S_{\text{hmin loc}}$, which shows a bimodal distribution.

$$S_c = \left( \frac{1}{2} \right) \sqrt{1 + \left( \frac{\sigma_1'}{\sigma_3'} \right)^2} - \frac{1}{2} \mu_i$$

Eq. 11

$S_c$ incorporates the differential stress represented by the first term and the mean stress represented by the second term to determine if shear failure will occur. $\sigma_1'$ and $\sigma_3'$ are the minimum and maximum effective principal stresses that have been reduced by the pore pressure and use the geologic convention of compression positive. These two stresses represent the effective $S_{\text{hmin}}$ and $S_{v}$ in a normal fault setting. $\mu_i$ is the internal coefficient of friction, and is taken to be 0.6. $S_c$ is an important and useful parameter for analyzing the potential for shear failure because if it is negative shear failure is inhibited, and when it is positive shear failure is enhanced. Also, as $S_c$ becomes more positive the range of optimally oriented fracture planes increases, predicting that a more diverse fracture population can slip, and thus promote increased connectivity.

The contour plots of stress show how stresses are concentrated when all the faults slip together, and reveal the strong influence of fault intersections on the local stress state. The contours of $S_{\text{hmin}}$ shows slight dilation on the inside of the right turning parts of the fault bends, one of which is located at the injection wells at Desert Peak (Figure 10a). $S_c$ is negative nearly everywhere in the reservoir, so shear failure is unlikely from a single fault slip event (Figure 10b). However, $S_c$ is slightly higher at the location of the injection and production wells. The tick marks indicating fracture orientations also show a resemblance to the other two faults in the fault relay that were not modeled (Figure 5.2.4c). Fault models that incorporated these two fault traces with the other three, one after the other and then both together did not significantly change the stress patterns in the model, and are therefore not shown here.

Figure 10: All three faults modeled together showing a) $S_{\text{hmin}}$ and b) maximum coulomb stress. Warmer colors indicate increases and cooler colors indicate decreases, and the tick marks show the orientations of preferred slip planes that resemble c) the other two faults not modeled in the relay.

DISCUSSION

Since the boundary element method allows complex fault geometries to be modeled in an infinite, non-discretized volume, one can effectively model the complex patterns of stress that result from detailed fault maps. While a conceptual structural interpretation is a critical element for understanding geothermal systems, it is still difficult to predict where and how stresses are being concentrated around a fault from the geometry alone, to assess the confidence in the model. The series of simulations at Desert Peak that explore parameter
uncertainty has consistently caused areas of increased rock failure potential from fault slip that correlates to active injection and production wells. Although conditions of rock failure were not achieved from the local stresses produced around the fault by elastic distortions accompanying slip, it is worth noting that this model represents a single slip event where the highest displacement on any given fault is ~1.0 meters. Some of the geologic surface contacts and cross sections imply up to 1500 meters of displacement, requiring multiple episodes of slip and superposition of local stresses. While stresses that cause fractures are only one of many important factors that govern the dynamics and life-cycle of a geothermal system, they play a critical role in the circulation of geothermal fluids, and thus this modeling method can aid in geothermal resource development that would avoid a blind ‘trial and error’ approach.

Although the data to constrain structures and stress state in the subsurface at Desert Peak are generally lacking, recently collected data from stimulation (Chabora et al., 2012) are available for comparison to the results of the fault models. Seismometer arrays placed at Desert Peak provide data on the location of fracture formation and slip from EGS stimulation that can be compared to the stress model to see if it can be used as a way to predict where increased porosity due to fracturing will develop due to injection into a well to lower the effective normal stress. Also, tracer tests performed at Desert Peak between injection and production wells have provided an inferred groundwater flow-path based on relative arrival times and concentrations in monitored wells (Rose et al., 2009). This pathway can be compared to the fracture patterns predicted by the model, assuming that active fractures are permeable (Barton et al., 1995, 1998) and provide preferred paths for fluid flow. Conversely, inactive fault segments as indicated by fault slip tendencies may preferentially inhibit fluid flow.

In November 2011 (E. Zemach, pers. comm., December 2011) an improved seismic network was placed at Desert Peak that is more sensitive and has a lower signal to noise ratio enabling complete earthquake detection to or slightly below zero (Figure 11). In the subsequently recorded seismicity catalog, there are two large clusters of small earthquakes each within a fault-bounded volume that contains an injection well, and a small cluster of larger earthquakes near the production well to the south. The proximity of the clusters of small earthquakes to geothermal wells implies they are induced by fluid pressure fluctuations due to pumping along the natural fracture network. If this is the case, then the resulting events reflect the combination of fractures as predicted by modeling in this manuscript, and localized fluid pressure from injection. In addition, the direction of model predicted fracture does appear to correlate with the trend of these clouds of seismic events, as well as the implied flow direction from NE to SW between injectors and producers. The small cluster of larger earthquakes to the south near the production well correlates with the increase in fracture potential from the stress model. This is also a location of a fault intersection where there is a high stress concentration from fault slip. However, if this is the only underlying mechanism that causes larger seismicity, then the other fault intersections should have larger earthquakes near them as well. Another possibility is that different populations of natural fractures and faults exist at these different locations. We postulate that all or nearly all induced earthquakes require these fractures to be in place to respond to the local stress changes. Another key mechanism is the difference of fluid pressure from injection and extraction as an important causal factor on increased porosity from EGS within the geological tectonic framework. The increase of fluid pressure at the injection wells would require a smaller differential stress to cause a fracture to slip, creating many small earthquakes. The reduction of fluid pressure from extraction at the production well requires a larger differential stress to cause slip on a fracture, which would cause more violent shearing and larger earthquakes, consistent with the pattern in the data.

Tracer tests were performed at Desert Peak to characterize flow patterns between injection and production wells (Rose et al., 2009). Two different tracers, 2,6-naphthalene disulfonate (2,6-nds) and 1,5-naphthalene disulfonate (1,5-nds), were injected into the two main injection wells at Desert Peak (the western DP 22-22 and the eastern DP 21-2) and the production wells to the south were monitored over a period of 110 days. These tests reveal an implied flow-path based on the arrival times of the tracers to the wells (Figure 12a). The strength of the connection is revealed in the breakthrough curves at each well by the time until breakthrough and the sharpness of the peak in the time versus concentration curve and is represented in Figure 12a. These characteristics correlate to the permeability and tortuosity of the path connecting injection to producer and whether flow is directly from one well to another or if there is leak-off to other volumes.

The flow-path implied by the tracer tests reveals a pattern of initial strong southward flow, shown by the strong concentration and prompt arrival (>250 ppb in ~6 days, Rose et al., 2009) of both tracers at well DP 74-21, followed by the later arrival
and smaller peak concentration at well DP 67-21 (20 ppb in 20 days, Rose et al., 2009). However, the tracers did not make it to well DP 21-1, which is slightly further south, and instead were detected in wells DP 77-21 and DP 86-21 towards the east (Figure 7.2.1 a).

This may be because the well is just south of the section of the westernmost fault that trends to the NW (Figure 7.2.1 b), which is roughly perpendicular to SHmax and has a much higher concentration of normal stress across it, causing it to have a reduced displacement and slip tendency (7.2.1c and d). A fault that is not well oriented for shear failure has less chance to slip and thus more time to ‘heal’ from the accumulation of mineral scale deposits in the fault that could ultimately reduce the permeability across it (Micklethaithe et al., 2010), implying compartmentalization of the reservoir. Although a decrease in permeability is generally undesirable in a geothermal field, this fault may play a productive role by laterally containing the reservoir fluid. The disruption of the strong southerly flow pattern makes the water from the injection wells slow down significantly, causing it to have an increased residence time in the reservoir, which makes it accumulate more heat. Alternatively, it implies pressure support is confined to the northern volume, and no additional heat is swept to DP 21-1.

![Figure 11: a) modeled maximum Coulomb shear stress as a proxy for shear failure potential, b) modeled Shmin as a proxy for tensile failure potential and c) locations and magnitudes of earthquakes at Desert Peak. There are two large clusters of small earthquakes tailing off the injection wells and a small cluster of larger earthquakes near the production well.](image1.png)

![Figure 12: a) Implied flow-path based on concentrations and arrival times of tracer 2,6-nds pumped into well DP 22-22 and 1,5-nds pumped into well DP 21-1 (Reproduced from Rose et al., 2009), b) fault traces at the reservoir depth and locations of injection wells and monitoring wells for the tracer tests, c) fault displacement and d) slip tendency.](image2.png)
CONCLUSIONS

The ability of a boundary element model to simulate fault slip and thus predict locations of stress concentration and secondary natural fault and fracture populations is highly dependent on the uncertainty of the model parameters. In most geothermal systems, and especially in blind geothermal systems such as Desert Peak that have no surface expression, these uncertainties are very large and represent a significant barrier to the development of these energy resources. Thus, rigorous sensitivity studies that explore and quantify the impact of these uncertainties to provide mechanically plausible models can be derived from systematic boundary element modeling of the role of large faults in geothermal systems such as those that make up the Rhyolite Ridge Fault System. In particular, these models show interaction among model parameters and can determine where more data are needed to better constrain the model or distinguish between competing models. This approach can help guide extrapolation of stress distribution over a large area from limited data sets, as well as assess confidence in the model prediction. By determining a model likelihood prediction based on the most commonly occurring model output, as well as the probability distribution that considers the misfit of observed data to the model output and existing data, one can make an informed selection of model input parameters based on the model that is best fit to multiple sources of data, or recognize the family of indistinguishable models.

While conceptual interpretations of fault systems and theoretical approaches to fault modeling can aid in testing the validity of structural interpretations of complex fault geometry, it is important to be site-specific when developing a stress model and consider stress magnitudes (rather than relying on ratios). Understanding the underlying mechanisms that concentrate stress at a particular site, such as fault overlap, can be used to test a conceptual model, as well as show how stresses and fracturing are being concentrated as the fault system develops.

The Rhyolite Ridge Fault System, when modeled with its mapped curvature shows how smaller length-scale geometric complexities along the fault system concentrate stresses locally that are not necessarily anticipated by the idealized conceptual model of fault overlap. Being site-specific with modeling parameters and fault geometry can lead to a predictive model that can aid in well site selection that would avoid a costly trial and error approach, by determining not only where porosity is being enhanced but also where it is reduced. Also, the low permeability of faults, or portions of faults implied by low slip tendency and displacement by the model of the Rhyolite Ridge Fault System could potentially determine if faults act as fluid conduits or baffles in a way that also incorporates hydrogeology, groundwater geochemistry and the mineralogy of the rock surrounding a fault.

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