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Uncertainty and Risk Evaluation During the Exploration Stage of Geothermal Development

Jeffrey B. Witter[1,2], Whitney J. Trainor-Guitton[3], and Drew L. Siler[4]

[1]Innovate Geothermal Ltd., Vancouver, BC Canada

[2]Department of Earth Sciences, Simon Fraser University, Burnaby, BC Canada

[3] Colorado School of Mines, Golden, CO, USA

[4] U.S. Geological Survey, Menlo Park, CA, USA

jeff@innovategeothermal.com, wtrainor@mines.edu, dsiler@usgs.gov

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ABSTRACT

Quantifying and representing uncertainty for geothermal systems is often ignored, in practice, during the exploration phase of a geothermal development project. We propose that this occurs potentially because the task seems so formidable. The primary goal of this paper is to initiate a dialogue within the geothermal community about: which geothermal uncertainties should receive the most attention and which uncertainty analysis methods could provide the greatest benefit for the advancement of the geothermal energy industry. In this paper, we discuss uncertainty quantification techniques that are applicable to geothermal exploration. In general, uncertainty associated with data acquisition/processing (i.e., objective uncertainty) is small compared to the uncertainty in interpretational space (i.e., subjective uncertainty) that lies between data points where extrapolation is required. Therefore, it is important to classify, assess, and quantify uncertainty to help select strategies to reduce uncertainty, and to better gauge the impact that separate uncertainties have on the overall likelihood of project success. In addition, geostatistics provides multiple quantitative methods for producing stochastic models which adhere to measured data and spatial correlation. The petroleum industry has successfully used both geostastistics and decision analysis methods to combine diverse and multiple types of uncertainties. We argue that instead of one single and final interpretation of the geothermal system, numerous interpretations may be more indicative of the possible subsurface scenarios, and these different scenarios can be evaluated using decision analyses and value of information methodologies. Lastly, we recommend that the potential power generation of a geothermal reservoir should be grounded in the geologic data and modeling for a specific field and their estimated uncertainties. In this paper, we provide a brief overview of many of these topics while a more complete review has been recently published in Witter et al. (2019).

1. INTRODUCTION

Due to the location of natural resources in the subsurface, there is an appreciable amount of risk and uncertainty associated with exploration for such resources whether they are petroleum, mineral, groundwater, or geothermal. Sound assessment and, better yet, quantification of exploration risk and uncertainty can inform important aspects of a resource exploration program such as: selection of drilling targets, estimation of resource volume, decision-making for allocation of limited exploration capital, as well as communication with potential investors and insurers. The characterization of project risk and uncertainty has been pursued extensively in the natural resource sector, particularly in the oil & gas industry, motivated by a desire to maximize the likelihood of project success.

An outline of the topics covered in this paper is as follows: 1) define the concepts of risk and uncertainty, including how they differ and 2) provide recommendations for research directions meant to improve our application of risk and uncertainty assessment to geothermal energy projects. Additional topics such as A) an overview of risk and uncertainty research that is relevant to the geothermal resource sector and B) a summary of approaches to characterize risk and uncertainty that have been used previously within the geothermal energy sector are discussed in Witter et al. (2019).

There is a strong need in the geothermal sector to reduce risk and uncertainty, especially in the exploration stage. Improving our ability to quantify and characterize geothermal resource risk and uncertainty would, ideally, lead to more successful projects. Risk and uncertainty analysis is a large field of study. For this paper, we focus primarily on uncertainty in the exploration stage of a geothermal project, encompassing geology, geophysics, temperature data, and initial drilling data, and how these can inform the early, conceptual ideas of a geothermal reservoir. In this review, we do not address production uncertainty or dynamic reservoir modelling as this lies beyond the scope of the present study. We do acknowledge that quantification of uncertainty at the production stage of a geothermal project is important, particularly where different stochastic history matching techniques may enlighten the flow behavior, especially for fractured media (de Marsily et al., 2005; Castagna et al., 2011). In addition, this paper does not discuss financial risk mitigation strategies for geothermal development. In recent years, the financial sector has excelled at addressing financial risk at some geothermal projects by utilizing different financial instruments to help get projects over the high-risk and costly hurdle of early stage exploration. Examples include the GRMF program for East Africa (Bloomquist et al., 2012) and the GDF program for Latin America (Wirth, 2018). Rather, in this paper we delve further upstream to explore the wide range of geoscience uncertainties, how to potentially quantify or characterize them, and how this affects project risk. Our motivation is to identify methods and approaches which might be best adopted by the geothermal sector. In summary, we contend that improved characterization of geothermal uncertainty will have a significant and beneficial impact on the risks associated with a geothermal energy development (Figure 1).

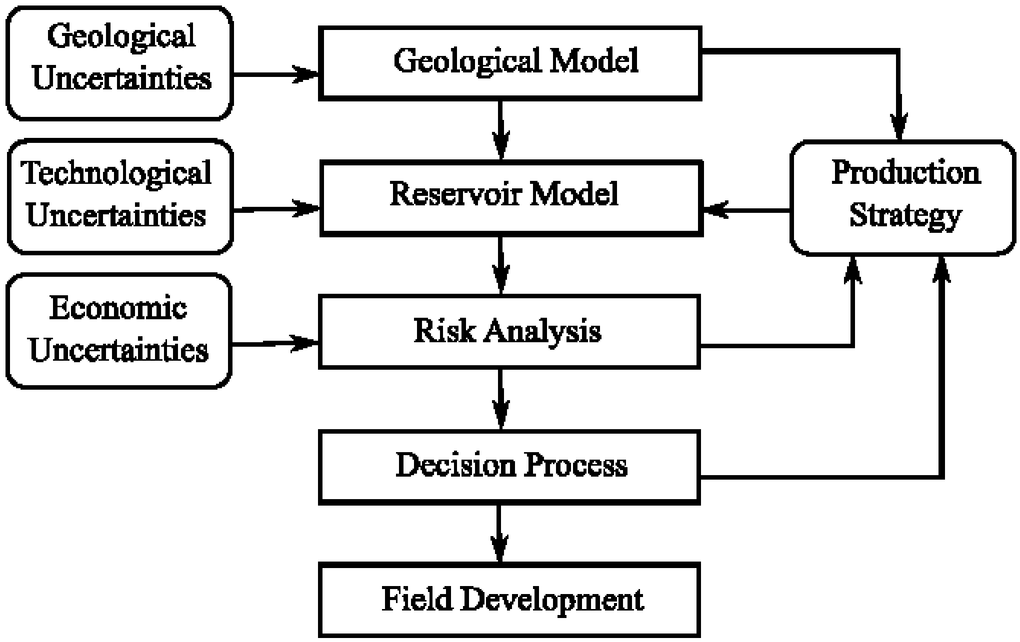

Figure 1: Flow chart showing typical geothermal resource development pathways including the relationship between uncertainty and risk. The focus of this paper is geological uncertainties (upper left in figure). A full assessment of technological uncertainty related to reservoir modelling is beyond the scope of this paper. Examples of economic uncertainties include the cost of drilling or the electric power purchase price. Diagram adapted from Schiozer and Suslick (2004).

2. BACKGROUND AND MOTIVATION

2.1 Definition of Risk and Uncertainty

To set the stage for this paper, natural resource sector-specific definitions of risk and uncertainty are useful to consider; in fact, they refer to two different concepts. Risk involves three elements: what can occur, with what probability, and with what consequences (often monetary outcomes) (Paté-Cornell, 1996). For example: *what is the percent chance that a well will be a dry hole (e.g. probability of no geothermal fluids)?* In probability theory, this is represented by the notation:

$$Pr(\Theta = \theta_i) \qquad (1)$$

where upper-case Theta represents the variable (e.g. reservoir) and lower-case theta is the discrete event (e.g. i=0 is dry and i=1 is not dry). Therefore, we can represent the perceived understanding of the risk of the reservoir of being dry as $Pr(\Theta = \theta_{i=0}) = 90\%$, where 90% is an example quantity, that could come from expert opinion, evaluation of historical cases, or some numerical evaluation, e.g. a Monte Carlo simulation. In some cases, risk is alternatively defined as the probability of the event multiplied by the financial outcome of that event and an action taken. The risk of drilling a dry hole would be computed as follows (Pratt et al., 1995):

$$Pr(\Theta = \theta_{i=0}) * \$[Cost\ of\ drilling] \qquad (2)$$

In contrast, uncertainty reflects “the inability to estimate a value exactly” (Ross, 2004). For example: *what is the uncertainty in the volume or permeability of a geothermal reservoir?* It is important to clearly distinguish risk from uncertainty to avoid confusion. In general, risk is something that we want to always minimize. But large uncertainty implies that there is both upside potential as well as a downside. For example, if there is large uncertainty in the volume of a geothermal reservoir, that is potentially good because the reservoir just may be bigger than the average value.

It is also important to understand the relationship between uncertainty and risk. Generally, individual project parameters have a certain degree of uncertainty associated with them and these various uncertainties are fed into an evaluation of risk. In other words, risk considers the impact of uncertainty on the application being assessed (Rossi and Deutsch, 2011). All natural resource projects have both risk and uncertainty. In addition, there are many different types of risk and uncertainty which we discuss in this paper. Furthermore, risk and uncertainty can be quite different at different stages of project development.

2.2 Types of Uncertainty

One of the challenges of the geosciences is the inherent problem of incomplete knowledge of the geologic and engineering properties (geologic geometries, temperature distribution, mechanical moduli, permeability, etc.) of the subsurface. Uncertainties have commonly been ascribed to one of two categories: epistemic uncertainty and aleatory variability (Paté-Cornell, 1996). This distinction was introduced into the geoscience parlance with probabilistic seismic hazard analysis (Budnitz et al., 1997). Epistemic uncertainty is a result of lack of knowledge. With additional observations epistemic uncertainties can be reduced and a more accurate value ascertained. For example, the epistemic uncertainty of the geometry of a fault system can be reduced by drilling a well that intersects the fault in the subsurface. Aleatory variability, conversely, is unpredictability due to inherent randomness. Aleatory variability is also a function of scale, with variability ranging from the size of an individual grain to field-scale, influencing unpredictability in the geologic aspects of a geothermal site. For example, the primary permeability of a stratigraphic unit may be approximated as a single value at the basin-scale, but at the well-bore scale it may be highly variable due to local stratification, grain-size, cementation, or fracture characteristics. Understanding these different types of geoscience uncertainty is important to guide where and how to expend effort to reduce uncertainty associated with an exploration project. Importantly, for the case of aleatory variability, the collection of more data may not always further reduce uncertainty.

2.3 Uncertainty in Geoscience Exploration

The numerous sources and types of uncertainty are a key challenge in subsurface exploration because, collectively, they influence project risk. Perhaps this quote summarizes it best:

> "[T]he accuracy and reliability of [subsurface] predictions are undermined by ubiquitous uncertainty, which arises from heterogeneity of subsurface environments, inadequate and insufficient knowledge…, and inadequate conceptual and mathematical representations of relevant processes. (Tartakovsky et al., 2012). "

Indeed, in geothermal energy projects, uncertainty lurks in the geological, geophysical, rock property, and well data that serve as the building blocks of a static 3D geologic map or conceptual model. These data may be collected by different people at different times and at different scales and they are often all integrated and merged together in a final interpretation which includes many assumptions (Zabalza-Mezghani et al., 2004). Similarly, separate sources of uncertainty will also exist in the inputs and outputs of a dynamic numerical reservoir model. In theory, for us to be certain about anything in the subsurface, the uncertainties in the input data should be minimized as much as possible every step of the way in order to minimize negative impacts on project risk. An ideal scenario could involve propagation of all uncertainties into a final conceptual model that quantitatively visualizes regions with high, medium, and low uncertainty. In practice, uncertainty cannot always be minimized due to time and data constraints. Similarly, comprehensive propagation and combination of all sources of uncertainty is complex. Instead, a better approach is to classify, assess, and quantify uncertainty in order to help select strategies to reduce uncertainty. This will help to better gauge the overall impact the separate uncertainties have on the likelihood of project success (i.e. risk).

In a recent paper, Bond (2015) reviews uncertainty in the interpretation of geologic structure based upon decades of experience and lessons-learned in oil and gas exploration. The observations and conclusions of Bond (2015) are summarized here as they are particularly relevant since structural geology can play a key role in exploration for geothermal resources.

In common practice, the geologic interpretation of an area of interest begins with the construction of a geological working model, either inside of a geologist's head or with a 2D or 3D software application, using both geoscience data and visuospatial reasoning skills. As more data are obtained, the working model is added to and improved. This technique generates a geologic interpretation in an environment of high uncertainty and results in working models that are inherently non-unique. Construction of multiple working hypotheses (models) has long been recognized as having a positive effect on interpretation outcomes (Chamberlin, 1965) but this is rarely done in practice because of limitations on time and also because, as humans, single 3D models are cognitively easier to contend with and defend.

Bond (2015) also describes cognitive biases that affect and influence uncertainty in geologic interpretation from the perspective of human psychology. Examples of four cognitive biases include (Krueger and Funder, 2004; Bond et al., 2008):

1. Availability bias (the most familiar model is preferred)
2. Confirmation bias (the interpreter seeks to confirm own hypothesis)
3. Anchoring bias (inability of the interpreter to change their mind about the interpretation)
4. Optimistic bias (the interpreter gives a positive spin on interpretation to get desired outcome)

Humans are good at applying conceptual analogues to data, but unfortunately, if the analogues don't fit the data then we typically try to fit them to our preconceptions and prior knowledge (i.e. experience and biases) which may not be the best approach (Bond, 2015).

Uncertainty in geoscience models comes from many different sources. A static geologic model constructed for geothermal exploration, whether a 2D cross-section or a 3D volume, is typically based upon multiple geoscience datasets. Each dataset has its own uncertainties from acquisition, processing, and interpretation (which, in practice, are generally not passed along in a cumulative or systematic manner). These uncertainties all exist before any model is constructed. Usually, uncertainty associated with data acquisition/processing (i.e., objective uncertainty) is small compared to the uncertainty in interpretational space (i.e., subjective uncertainty) that lies between data points where extrapolation is required. For the case of 3D geologic modelling, the outcome is commonly a combination of subjective interpretation with extrapolation and mathematical interpolation of "hard" data (e.g. well data) to make 3D geologic surfaces. In addition, it is important to appreciate that different interpreters (with different prior knowledge and biases) can reach different conclusions from the same geoscience data (e.g. Bond et al., 2007) which adds further uncertainty.

Oftentimes, dynamic geothermal reservoir models are based upon information from static geologic models. Uncertainty in the static models, therefore, serve as a source of uncertainty in the reservoir model (Bond, 2015). If the uncertainties in the original static geologic model are not quantified and/or not passed along to the reservoir modelling team, it can be difficult to accurately assess the uncertainty in the reservoir model output.

Importantly, the uncertainty in some parameters will matter, but others will not. For example, the level of uncertainty in some input parameters may be so small compared to others to be rendered negligible. Alternatively, large-scale uncertainties may occupy portions of the 3D model space which are less important to project development and are therefore insignificant. One strategy to deal with these uncertainties is to build multiple static geologic models as inputs to the dynamic reservoir model. Such a technique is time-consuming but it can be very useful to help define the uncertainty space (Bond 2015). Schiozer and Suslick (2004) argue for the construction of several different geologic models that are "representative" of the geological uncertainty which are then used as input for the reservoir modelling. By taking this approach, the dynamic modelling exercise effectively translates geological uncertainty to risk by converting a 3D geologic framework and thermal fluid flow into a probability of energy generation in units of MW (which is then convertible to revenue). If it is possible to translate uncertainty into risk in this manner, then it is easier to determine which geologic/reservoir uncertainties cause the greatest risk for the decision-maker and have the greatest impact on the financial outcome of the project. This will be developed further in the next section on Decision Analysis.

3. DECISION ANALYSIS: FOCUS ONLY ON UNCERTAINTIES THAT INFLUENCE THE "BOTTOM LINE"

As described above, the current practice in the geothermal sector is to focus on identifying in advance the probability and MWe capacity of geothermal power production prior to construction of a power plant. However, as we have discussed in previous sections, the large number and types of uncertainties in geothermal resource exploration can be daunting – and these uncertainties likely control the probabilities of geothermal power potential. Geoscientists and engineers could devote an enormous amount of time and energy on the task of providing a comprehensive evaluation of uncertainty in 3D subsurface models. However, a better approach is to prioritize uncertainty quantification to those subsurface (geologic) parameters that are most influential to the success of exploration and development stages of the project. In other words, to be most efficient, it is prudent to focus on the parameters in the multiple model constructions (i.e. interpretations) that affect the financial outcome of the project. From a project success perspective, it may be safe to disregard all the other sources of geoscience uncertainty that are not as significant in order to focus effort on the most important ones.

The crux of uncertainty assessment for the development of a geothermal resource ***is the ability to translate uncertainty into risk.*** It is imperative to determine how each unknown affects the effort to harness geothermal energy. For example, for many geothermal systems, the reservoir's permeability, temperature, and volume will be the most influential or consequential parameters that control power production. In many geothermal areas, subsurface temperature distribution is controlled by fault structures that serve as geothermal fluid pathways. Similarly, permeability is a function of lithology as well as geologic structure. Also, the volume of a geothermal reservoir is often controlled by the 3D lithologic and structural framework (e.g. bounded by impermeable faults and/or clay caps). Our knowledge of the temperature, permeability, and volume is then directly tied to our 3D geologic understanding of the geothermal system. Therefore, accurately quantifying the likelihood of all possible values of permeability, temperature, and volume (and related resource-specific properties) should be a high priority and may take precedent over uncertainty analysis of less consequential parameters. An established methodology to address such issues lies in the field of decision analysis (Howard, 1966; Pratt et al., 1995).

Decision analysis provides systematic methods for incorporating the various types of uncertainty described above, and it has been widely adopted in the oil and gas industry (Bratvold et al., 2009). The quantitative axioms of decision analysis promote logical, evidence-based decisions with the intent of improving the probabilities for successful outcomes, *e.g. whether or not to drill a geothermal well and/or where is the best location to place the well?* The founders of the decision analysis discipline justify its importance in conquering the "lizard" or primitive part of our brain. As described in recent and popular books on the psychology of decision making (e.g. *Moneyball* (Lewis, 2003), *Thinking Fast & Slow* (Kahneman, 2011)), humans are constantly fighting our evolutionary history of making decisions with our "gut" (more specifically our older, more survival-focused lizard brain) versus with our quantitative and logical pre-frontal cortex. To help remove the influence of "lizard brain", decision analysis provides methodologies that both take advantage of risk calculations and provide analysis for using several subjective interpretations (e.g. multiple geologic models, working hypotheses or interpretations).

Decision analysis concepts are often described in terms of lotteries and prizes (Pratt et al., 1995). By choosing to drill or not, a decision maker is choosing whether or not to participate in a lottery with certain perceived chances of winning a prize (drilling into a profitable reservoir); however, this lottery also involves the chances of losing money (drilling into an uneconomic reservoir). Decision analysis requires a probability density function or empirical histogram of important uncertain parameters; as a demonstration example for this paper, we will use permeability and temperature given below. This is shown graphically in **Error! Reference source not found.**. The probabilities for each possible discrete outcome (e.g. high or low temperature) are assigned to their respective "branches" on the decision tree. The branches could represent other uncertain geothermal indicators.

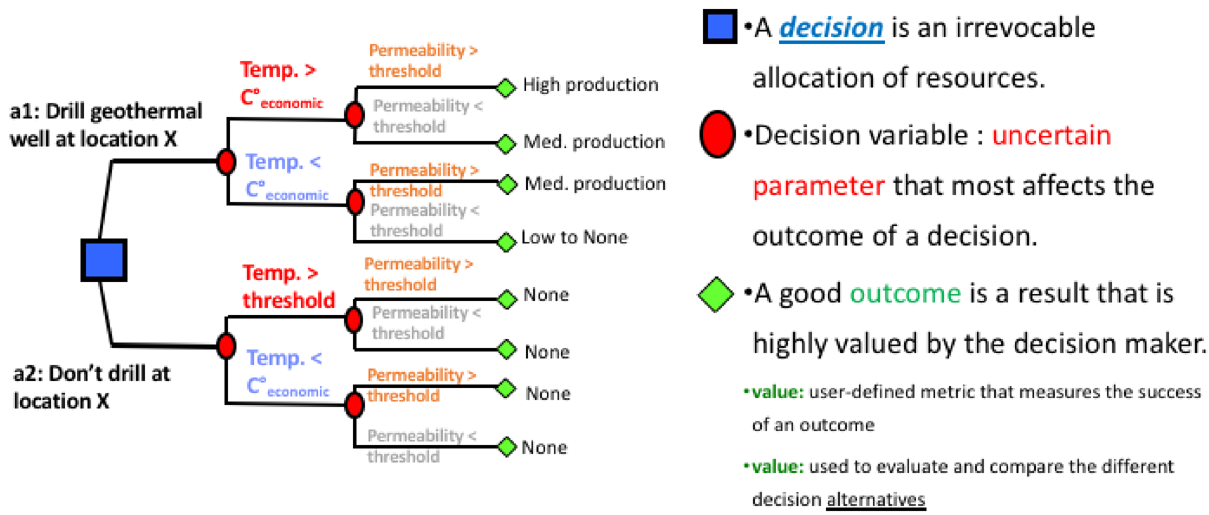

Figure 2: Example Decision Tree representing alternatives to drill a well or not (blue square) and two uncertain decision variables (red ovals): temperature and permeability.

Trainor-Guitton et al. (2013) give uniform probability density functions for permeability and temperature. Decision analysis then calculates the average risk for any possible decision alternative (e.g. drill or don't drill, represented in Equation 3 respectively by *a=1* and *a=2*) and provides which alternative is more logical given the highest-valued on-average outcome (e.g. the *max* operator in Equation 3). Thus, the prior value (*Vprior*) advises when one should participate in this "geothermal lottery" (i.e., drill a well) given both the prior uncertainties ($Pr(\Theta = \theta_i)$) and possible gains and losses (v_a). Simply put, it identifies the decision choice that has the highest, average financial outcome, given the uncertainty of the possible "geologic" events. This is depicted mathematically:

$$Vprior = \max_a \left(\sum_{i=1}^{N} Pr(\Theta = \theta_i) v_a(\theta_i) \right) \quad a = 1,2; \;\; i = 1,..,N \tag{3}$$

An important note is that the discrete event represented by θ could represent the P10, P50 and P90 values of a property (i.e. 10th, 50th and 90th percentile of temperature or permeability) or end member interpretations (e.g. locations of faults).

Within decision analysis is the measure of another parameter called 'value of information'. It evaluates whether new information can increase the average highest outcome over *Vprior* by updating our uncertainty of certain geologic events: $Pr(\Theta = \theta_i)$. Trainor-Guitton et al. (2017) proposes a methodology for calculating the value of information derived from a magnetotelluric survey and resistivity model. The methodology includes several interpretations of the clay cap and the variability of electrical conductance within the cap that are within a certain radius from observed steam flow rates.

There are only a few examples in the literature of the application of decision analysis to improve geothermal exploration and development outcomes (Trainor-Guitton et al., 2014, 2017). Appropriate use of decision analysis in the geothermal sector could contribute to improvement of currently used "heat-in-place" and "power density" methods.

4. NEW DIRECTIONS

4.1 Geostatistics: Quantifying Spatial Uncertainty

The field of geostatistics originated from the mining industry with the intention of improve mining outcomes. In its beginning, geostatistics aimed to quantify the spatial correlation into interpolations of the ore grade (Matheron, 1971; Journel and Huijbregts, 1978). We present geostatistics in this paper because, to our knowledge, it is underutilized in the geothermal sector and could be useful to better quantify uncertainty. For most geoscience applications, the data sampled are from sparse boreholes. Therefore, spatial interpolation is needed to obtain maps or models which estimate how properties of interest (e.g. permeability, temperature, etc.) change in the 3D subsurface. Standard interpolation techniques (e.g. linear, nearest neighbor, etc.) do not allow for higher correlation horizontally versus vertically, which is usual for geologic strata, nor could one account for higher spatial correlation in the direction of the depositional process. Geostatistics allows for 3D interpolations that adhere to geologic bedding, strike, and dip.

This "geologic" interpolation is known as Kriging and utilizes the variogram. The variogram is the original metric of spatial correlation in geostatistics. Variograms can account for 2D or 3D anisotropy by identifying azimuths of highest spatial correlation. For geothermal applications, sparse permeability or temperature measurements may have spatial patterns that follow bedding, and thus can be captured quantitative by a variogram. Perhaps more importantly, Kriging maps are generated such that the spatial interpolation is informed by the variogram (Isaaks and Srivastava, 1989; Deustch and Journel, 1998). Figure 3 contains two Kriging models with different spatial correlation structure, information that is contained in the variogram. Williams and DeAngelo (2011) provide an example of Kriging used to interpolate subsurface temperature measurements in geothermal.

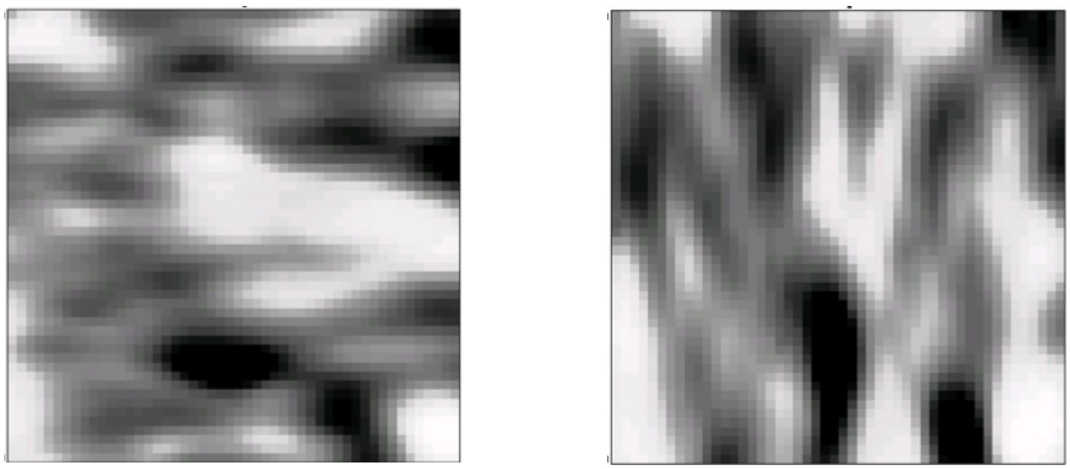

Figure 3: Two Kriging Models: using a variogram with a) high East-West spatial correlation and b) high North-South spatial correlation

Importantly, for petroleum applications of reservoir flow simulation, stochastic versions of the Kriging methods exist and produce many "equi-probable" realizations or sample models (e.g. Sequential Gaussian Simulation, Direct Sequential Simulation, see Remy et al. (2011)). These models reproduce the variogram characteristics, thus not creating overly smooth Kriging models. Thus, it captures a better global heterogeneity that has historically been used in petroleum production history matching (Hu, 2000). Most importantly, these numerous realizations can then serve as an uncertainty measure in 2D or 3D space of the estimated properties. However, depending on the scale of heterogeneity or conceptual model being characterized, these approaches may be too simplistic and/or the stationarity requirement (homogenous statistics over the model area: e.g. mean, variogram) may not be valid (Isaaks and Srivastava, 1989). To the knowledge of the authors, there are two applications in peer-review literature of stochastic realizations used to represent geothermal parameter uncertainty. Vogt et al. (2010) utilize stochastic geostatistical methods to capture the spatial heterogeneity of thermal conductivity. Niederau et al. (2017) explore three different permeability scenarios (different distributions) via stochastic simulations and its effect on hydrothermal flow convection.

The field of geostatistics has evolved to include more complex spatial features, which attempt to mimic the geologic processes that create important heterogeneity. Modeling techniques include training images for multiple-point statistics, object-based and lastly, process-based modeling. These are listed from least to most geologically realistic and easiest to hardest to condition to data. Training images are conceptual representations of the heterogeneity patterns such as alluvial fans, sinusoidal fluvial streams, etc. (Strebelle, 2002). Respective examples or reviews for each of these can be found in: Hu and Chugunova (2008), Matheron (1971), and Koltermann and Gorelick (1996). Hybrids of these groups have also being proposed (Deutsch and Wang, 1996; Michael et al., 2010; Linde et al., 2015). These methods have largely been used in sedimentary systems, however, they could be useful for certain geothermal scenarios where repetitive structures could be generated stochastically. One potential scenario is orthogonal fault sets and their respective joints and fractures could be represented in this manner.

Other geologic features or structures important for geothermal exploration or development can be represented with a training image. Carranza et al. (2008) describe how spatial trends in volcanic rocks, quasi-gravity lows, and faults had a strong correlation with geothermal indicators. Thus, these types of recurring geologic existences can potentially be modeled with training images. However, many aspects of complex geothermal systems may not adhere to the repetitive patterns that are necessary for a training image and will not lend themselves to object-oriented or multiple point statistical approaches. Stationarity deems that the statistics are homogeneous such that spatial inferences can be made in the form of Kriging and stochastic simulations (Strebelle, 2002).

5. DISCUSSION

In geothermal exploration, as in analogous subsurface industries, subjective uncertainty (i.e., uncertainty in geological interpretation), rather than objective uncertainty, is likely to have the most significant effect on the final interpretation of the most important geothermal factors, i.e., temperature, permeability, and volume. Additionally, both epistemic uncertainty (resulting from lack of knowledge), and aleatoric variability (natural randomness at a variety of scales) can impart uncertainty that is relevant to decisions made during resource exploration.

Temperature, permeability, and volume are the three subsurface parameters that are most critical to constrain a geothermal resource. The distribution and localization of permeability in geothermal systems is heavily dependent on lithologic distribution and geologic structure (Flóvenz and Sæmundsson, 1993; Bibby et al., 1995; Curewitz and Karson, 1997; Rowland and Sibson, 2004; Faulds et al., 2006, 2011; Wallis et al., 2012). Thus, uncertainty in a 3D geologic model can translate into uncertainty in geothermal reservoir permeability. A complete 3D statistical analysis of multiple structural geometries (e.g., Wellmann et al., 2014) may not be feasible for a variety of reasons. Still, reduction of subjective uncertainty in a geologic interpretation, employing multiple working models/hypotheses (e.g., Wellman et al., 2010; Schiozer and Suslick, 2004; Bond, 2015) is crucial. Similarly, generating multiple, complete seismic reflection, or gravity interpretations, is ideal, but may not be feasible due to time, computational and cost constraints. But allowing for the possibility of multiple end-members (e.g., shallow fault-dip case vs. steep fault-dip case) and evaluating whether each is permissible within an internally-consistent interpretation of the data helps avoid bias and can be used to define the 'uncertainty space', or the range of potentially valid interpretations (e.g., Bond, 2015, Lindsay et al., 2012). In situations in which data are collected in series, a concerted effort to avoid availability, confirmation, and anchoring bias is crucial. The existing interpretation should not be refined with respect to the new data, but rather a new interpretation should be developed incorporating all available data.

Understanding the scale of resolution of the data sets is important as well. For example, at scales below the resolution of a magnetotelluric resistivity inversion model (~10s-100s of meters depending on depth) or magnetic data (dependent on line spacing and increasing with depth), uncertainty associated with aleatoric variability can be significant. At fine-scales, variability in the fracture characteristics or cementation of an individual fault zone may constitute a large portion of the uncertainty in the permeability.

Cross-section restoration (e.g., Groshong et al., 2012; Butler, 2013) and geophysical inversion modeling (Witter et al, 2016; 2018) are also useful ways to the minimize subjective uncertainty of the final interpretation with respect to either geologic principles or an independent data set (i.e., rock density properties in the case of gravity inversion).

Temperature is the other critical factor in geothermal exploration. Shallow temperature gradient data, deep temperature gradient data, 2-m temperature anomaly data, and temperatures measured or calculated through geothermometry on surface or subsurface fluid samples need to be integrated in order to define temperatures of a geothermal system. Temperature contour maps, temperature contours on 2D sections, and 3D temperature models can all be extremely useful in geothermal exploration, but all are interpretive to some degree, and therefore are strongly affected by subjective uncertainty. Epistemic uncertainty, especially at reservoir levels, where data are likely to be most sparse (yet most crucial for geothermal exploration), certainly comes into play, as well as aleatoric variability. The stochastic simulation approach, used in mining and O&G and described in the Geostatistics section, may be appropriate for some geothermal reservoirs.

As described in this paper, geostatistical approaches have been successful at accounting for spatial uncertainty for the petroleum and mining industries for over 50 years. Not all the methods are appropriate for geothermal parameters, but some of these techniques could provide more agnostic and quantitative risk assessments of different geothermal indicators.

The authors contend that decision analysis and value of information provide a mechanism to focus data collection and modeling efforts on the geologic parameters that will most influence the success of a geothermal field. These tools provide a methodology that can bring the expertise of geologists, geophysicists and stakeholders together, which could provide a meaningful improvement over the currently used statistical methods of potential power generation. Both decision analysis and value of information methodologies allow for the propagation of all uncertainties into a final conceptual model. Assessing uncertainties for individual components, especially geological or geophysical information, has been a challenge, but new machine learning approaches may allow for computationally feasible evaluations of uncertainty.

6. SUMMARY AND CONCLUSIONS

- Risk and uncertainty are different: risk is associated with the probability of success while uncertainty is the inability to define something exactly. All geothermal projects have both risk and uncertainty. Multiple sources of uncertainty combine to have an impact on the evaluation of risk.

- Uncertainty is pervasive in geoscience exploration. It should not be ignored.

- Geologic models generally hide the extent and nature of uncertainties in the data and the model. As such, a typical geologic model is commonly misconstrued as being more certain than it actually is.

- To combat the uncertainty problem, it is important to: 1) generate multiple model realizations to capture the uncertainty and 2) visualize the model uncertainty (e.g. Siler et al. 2016, 2018; Wellmann & Regenauer-Lieb 2012).

- Although subjective uncertainties are hardest to quantify, they may have the most impact on the MWe estimates of geothermal resources.

- We suggest that once more exploration data is available, geologic parameters with a higher influence on geothermal production (e.g. financial outcome) should take priority and precedent over uncertainty analysis of less consequential parameters. This, in itself, is not always a straightforward relationship, but sensitivity studies and case studies could be one method for ascertaining the top parameters.

- Decision analysis and value of information should be utilized to help address challenges in geothermal exploration and development.

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