The value of spatial information for determining well placement: A geothermal example

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ABSTRACT

We have developed a spatial, value of information (VOI) methodology that is designed specifically to include the inaccuracies of multidimensional geophysical inversions. VOI assesses the worth of information in terms of how it can improve the decision maker’s likelihood of a higher valued outcome. VOI can be applied to spatial data using an exploration example for hidden geothermal resources. This methodology is applicable for spatial decisions for other exploration decisions (e.g., oil, mining, etc.). This example evaluates how well the magnetotelluric (MT) technique is able to delineate the lateral position of electrically conductive materials that are indicative of a hidden geothermal resource. The conductive structure (referred to as the clay cap) represented where the geothermal alteration occurred. The prior uncertainty of the position of the clay cap (drilling target) is represented with multiple earth models. These prior models are used to numerically simulate the data collection, noise, inversion, and interpretation of the MT technique. MT’s ability to delineate the correct lateral location can be quantified by comparing the true location in each prior model to the location that is interpreted from each respective inverted model. Additional complexity in the earth models is included by adding more electrical conductors (not associated with the clay cap) and deeper targets. Both degrade the ability of the MT technique (the signal and inversion) to locate the clay cap thereby decreasing the VOI. The results indicate the ability of the prior uncertainty to increase and decrease the final VOI assessment. The results also demonstrate how VOI depends on whether or not a resource still exists below the clay cap because the clay cap is only a potential indicator of economic temperatures.

INTRODUCTION

Earth scientists inherently see the value of geophysical data; they appreciate that knowledge, although imperfect due to noise, resolution limitations, the challenges of inversion, etc., is gained over the previous incomplete state of information. Geophysical surveys provide spatial coverage that sparse, expensive wells cannot. In many situations, however, it may be difficult to objectively quantify and demonstrate to decision makers if knowledge has been (or can be) gained. A methodology known as value of information (VOI) objectively quantifies the value of a particular information source by appraising its relevance and reliability. VOI provides a metric that derives from the field of decision analysis and declares that an information source has value if it can improve a decision maker’s probability of making decisions with higher valued outcomes (Howard, 1966; Pratt et al., 1995).

Bratvold et al. (2009) provide a review of the applications of VOI in the oil and gas industry, which includes some VOI demonstrations for geophysical data. Houck and Pavlov (2006) and Houck (2004, 2007) use reservoir models to evaluate the value of seismic amplitude data, controlled-source electromagnetics (CSEM), and 4D seismic data, respectively. Pinto et al. (2011) evaluate the VOI of 4D seismic for two discrete reservoir cases. A very important shortcoming of these examples is that they do not include geophysical inversion in their assessment of the reliability of the techniques to delineate the subsurface features or properties of...
interest. In other words, the VOI assessment does not include how the spatial distributions or locations of reservoir parameters may be distorted by the effects of noise, data sampling, model parameterization, and regularization (smoothing), on the inverse image. This will affect the reliability of the information from geophysical sources when the information is being used for spatial exploration decisions (i.e., where to drill).

Recently, emphasis on spatial uncertainty has been demonstrated for VOI assessments of geophysical techniques. Eidsvik et al. (2013) extend the work of Eidsvik et al. (2008) to include closed skew normal rock physics distributions. Bhattacharjya et al. (2010) present a VOI methodology for spatial decisions, where the spatial dependence of reservoir sands and shales is modeled as a Markov random field, and the value of seismic data is estimated for informing drilling decisions. Trainor-Guitton et al. (2011, 2013a, and 2013b) include spatial uncertainty of aquifer properties for evaluating the VOI of different geophysical techniques for groundwater sustainability decisions. However, none of these studies include multidimensional geophysical inversions, and therefore, the uncertainties introduced by inversion were not included in the VOI assessment. This is significant because 2D or 3D inversion and interpretation make it possible for geophysical information to aid in spatial decision-making. A spatial decision can be defined as any decision whose outcome depends on the spatial distribution of some property (Trainor-Guitton, 2010).

We present the first VOI methodology that includes the multidimensional nature of geophysical information with interpretation. Our methodology recognizes that often the raw data from a geophysical source are not useful for spatial decisions; thus, the geophysical “information” will typically consist of the data, the inversion, and the interpretation to link the geophysical attributes to a parameter that would directly affect a decision outcome (e.g., a geologic horizon or unconformity). Here, we present a VOI analysis that is applicable to decisions related to spatial exploration such as “where to drill”?

Figure 1 graphically depicts the concepts behind VOI. Let us consider we are faced with some generic decision to most effectively exploit a subsurface resource (e.g., oil, minerals, gas, water, etc.) and the largest uncertainty is the resource’s location. The horizontal axis from left to right represents lower to higher gains (utility or monetary returns) as outcomes from this generic decision. The lowest expected outcome (or calculated average) of the decision is shown to be when uncertainty is ignored (Figure 1a). For example, we could choose to disregard our ignorance (or our uncertainty) regarding the location of some subsurface resource. The next higher expected outcome (to the right) occurs when the current information and its uncertainty are accounted for when making the decision (Figure 1b). We will call this quantity the prior value $V_{\text{prior}}$ (a complete list of symbols used is given in Table 1). Current information could represent the geologist’s perspective on the likely locations of the resource. Next, we consider the highest expected outcome (furthest right oval: Figure 1c), which is possible when “perfect information” is available before making our decision. We will call this quantity the value with perfect information: $V_{\text{perfect}}$. This concept conjectures that an infallible tool or information source exists such that

![Figure 1. The outcome-uncertainty continuum that graphically represents the concepts behind VOI. Modified from Institute of Medicine (2013).](image)

### Table 1. Table of symbols.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>$x$</td>
<td>Clay cap location</td>
</tr>
<tr>
<td>$i$</td>
<td>Index of clay cap locations</td>
</tr>
<tr>
<td>$N$</td>
<td>Total number of considered clay cap locations</td>
</tr>
<tr>
<td>$a$</td>
<td>Decision alternative</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Existence or nonexistence of resource</td>
</tr>
<tr>
<td>$v$</td>
<td>Value: metric to define outcome of decision</td>
</tr>
<tr>
<td>$z$</td>
<td>Vector of earth parameters</td>
</tr>
<tr>
<td>$t$</td>
<td>Index of different realizations of noise added to the same forward response</td>
</tr>
<tr>
<td>$T$</td>
<td>Total number of noise realizations for one clay cap model</td>
</tr>
<tr>
<td>$g_d(\cdot)$</td>
<td>Decision predictor/function (e.g., drilling)</td>
</tr>
<tr>
<td>$f(\cdot)$</td>
<td>Geophysical forward modeling (i.e., MT simulation)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Electrical resistivity model</td>
</tr>
<tr>
<td>$d$</td>
<td>Synthetic data</td>
</tr>
<tr>
<td>$\tilde{d}$</td>
<td>Synthetic data with noise</td>
</tr>
<tr>
<td>$h(\cdot)$</td>
<td>Inverted electrical resistivity model</td>
</tr>
<tr>
<td>$\tilde{x}$</td>
<td>Automatic interpretation function</td>
</tr>
<tr>
<td>$j$</td>
<td>Interpreted location of clay cap</td>
</tr>
<tr>
<td>$V_{\text{prior}}$</td>
<td>Prior value</td>
</tr>
<tr>
<td>$V_{\text{perfect}}$</td>
<td>Value with perfect information</td>
</tr>
<tr>
<td>$V_{\text{imperfect}}$</td>
<td>Value with imperfect information</td>
</tr>
<tr>
<td>VOI_{imperfect}</td>
<td>Value of imperfect information</td>
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</table>

(2008) use statistical rock physics models and spatial dependence within a VOI framework to decide whether or not to drill for oil. Spatial dependence is included in the 2D grids representing the porosity and saturation of the reservoir through a covariance model. At each of the grid locations, CSEM and seismic amplitude variation with offset data are drawn from likelihood models that represent the link between the reservoir properties and the geophysical attributes. Their method attempts to preserve spatial dependence through the spatially correlated porosity and saturation field. Rezaie et al. (2014) extend the work of Eidsvik et al. (2008) to include closed skew normal rock physics distributions.
it perfectly reveals (without error or noise) the location of the sought-after resource. In other words, with perfect information, we will always place a well in exactly the right place to recover the resource.

By comparing $V_{\text{perfect}}$ (Figure 1c) and $V_{\text{prior}}$ (Figure 1b), one can quantify if there is an increase in the expected outcome when making the decision with perfect information versus the current information. This potential increase is the value of perfect information $\text{VOI}_{\text{perfect}}$. Therefore, in its simplest form, the VOI equation can be expressed as

$$\text{VOI} = V_{\text{with information}} - V_{\text{prior}}. \quad (1)$$

Equation 1 makes some assumptions about the decision maker's risk tolerance and utility function (Raiffa and Schlaifer, 1961). The VOI expression (as shown in Figure 1) compares the average decision outcome made with the proposed information to the average decision outcome made without it. Value $V$ is the metric used to quantify the outcome of a decision; the higher the value, the more successful an outcome of a decision is. Usually, this is in monetary terms but it could also be in physical quantities (barrels of oil produced, BTUs produced, etc.). The VOI of a particular technique in monetary terms can then be compared with the cost of acquiring that information; if the VOI is greater than the cost, it is deemed a good decision to purchase that information.

The value with imperfect information ($V_{\text{imperfect}}$) is represented by the oval of Figure 1d. This quantity accepts that the message from the interpreted geophysical data (e.g., seismic, CSEM) will not always accurately identify the location of the resource. Therefore, this quantity is depicted as lower valued (to the left in Figure 1) compared to the value with perfect information ($V_{\text{perfect}}$, Figure 1c). The value of imperfect information $\text{VOI}_{\text{imperfect}}$ can be quantified by comparing it to $V_{\text{prior}}$. In other words, if you can account for the inaccuracies of the information source and demonstrate that it would still increase the expected outcome over a decision made with the current information, the imperfect information will be a deemed valuable (equation 1).

To obtain a $V_{\text{perfect}}$ measure, one must estimate the reliability of the information source. Bratvold et al. (2009) describe how quantitative methods are needed to evaluate the information reliability. We will consider the reliability of the geophysical source to spatially resolve a resource target. Our approach includes the effects of the inversion image resolution and its impact on the information reliability. Therefore, we include spatial uncertainty in the VOI methodology thereby improving the VOI metrics used for exploration decisions.

**Hidden geothermal resource**

We demonstrate our spatial VOI methodology using a hypothetical geothermal exploration example. We suggest that our methodology is transferable to other applications. Our example is motivated by Cumming (2009), who conceptualizes hidden (or blind) geothermal resources. Figure 2 demonstrates a possible hidden geothermal resource in which no surface expression exists to indicate a possible geothermal resource. His model (Figure 2) demonstrates a scenario where faults and fractures allow for the circulation of hot water to accessible depths. As a result, smectite and illite clays are formed just above the shallowest depths where the hot water circulates.

Similar to oil exploration, the geothermal community has employed geophysical surveys to characterize the subsurface with the intention to improve its knowledge of subsurface reservoirs and to reduce their exploration risks. Direct current electrical resistivity and self-potential techniques have been employed to decipher potential flow paths for hot water (Richards et al., 2010), whereas microseismic traveltimes (Wu and Lees, 1999) and magnetotelluric (MT) data (Garg et al., 2007; Newman et al., 2008) have been used to infer the 3D geologic structure of geothermal areas.

Also, like oil exploration, geothermal prospecting with geophysical techniques is complicated by challenges related to the nonunique relationship of geophysical attributes in the subsurface and the geothermal reservoir parameters. Historically, the MT technique has been used to delineate zones of materials with low electrical resistivity that can be indicative of alteration caused by the circulation of hot fluids (Gunderson et al., 2000). This alteration is often referred to as the clay cap, and we adopt this terminology here. However, low-resistivity zones can also be created by the presence of brines and/or clay-rich sediments (Ucok et al., 1980; Newman et al., 2008). Another complicating factor is that the clay cap alteration reflects the historical high temperature of the system. Therefore, the existence of clay cap does not ensure that economic temperatures still exist below it. Karlssdóttir et al. (2012) describe how the resistivity alone cannot confirm a viable geothermal resource.

Figure 3, also from Cumming (2009), provides a conceptual model of electrical resistivity for the geologic representation of Figure 2. The hidden resource is at the apex of the isotherms, which coincides with the concave side of the 10-ohm-m clay cap (light gray). Therefore, for our modeling and VOI demonstration purposes, this clay cap is the key potential indicator of the resource. Specifically, we want to locate the lateral position of the clay cap throat, that is, the more resistive location where the clay cap narrows. According to Figure 3, the clay cap throat indicates where
the fault will allow for the shallowest access to flowing, hot liquids. Therefore, the throat of the clay cap (here forward also referred to as the *throat*) is our proxy target for drilling.

**Information source considered: Magnetotellurics**

Given these challenges, we consider how well the MT technique can help determine the lateral location of the clay cap throat. Please see Vozoff (1991) for a discussion of the basics of the MT measurement. MT has strengths and weaknesses when used to explore for geothermal resources. The MT measurements may help determine where a clay cap exists, but they cannot tell definitively about the temperature below the cap. Additionally, the cap’s lower electrical resistivity tends to shunt electrical currents and greatly reduces sensitivity to the properties of the deeper reservoir or around the throat. The VOI method described here will allow us to quantify MT’s usefulness (spatial coverage and sensitivity to low-resistive clays) and limitations (low resistivity is not uniquely associated with higher temperature, i.e., whether a resource exists).

Thus, the work presented here will use this geothermal example to demonstrate a spatial VOI methodology. The next section (“Problem description”) describes how the prior uncertainty of the subsurface (i.e., the state of knowledge before the MT survey data are available) is represented with simplified geothermal reservoir models that represent different possible locations of the resource. The next section will also describe $V_{\text{prior}}$, which captures the expected outcome of a decision taken without the benefit of MT data. In the “Methodology” section, we devise a method for estimating MT’s reliability to determine the location of the geothermal reservoirs. This step involves simulating the MT response using the prior models and inverting these data to construct electrical resistivity images. This section also describes how the value with imperfect information ($V_{\text{imperfect}}$) is calculated using the MT response. The “Results” section presents the value of imperfect information results for several different reliabilities and priors, along with complexities added to the prior models. Through the decision uncertainty and the models included in the prior, we will demonstrate how VOI can underscore the strengths and weakness of a particular information source.

**Problem description: Uncertainty of possible hidden resource (clay cap throat) location and where to drill?**

Figure 4 shows a decision tree that depicts the decision scenario that we have described. The tree represents the decision-to-outcome process chronologically from left to right. First, a decision of where to drill is taken (extreme left). The final outcome (extreme right) will depend on where the resource is (as indicated by the clay cap location) and if a resource exists under the cap. The decision tree convention is that decisions (e.g., drilling) are represented with square nodes, uncertainty nodes (e.g., clay cap existence and location) are oval, and the value outcomes (profits or losses) are the diamond nodes. For this work, we only consider how the MT source can help detect the location of the throat. In the “Results” section, we will introduce how we account for the probability of the resource existing (represented by $P(\Theta = \theta_j)$) given the existence of the clay cap.

To represent our uncertainty in the location of the clay cap, we create prior models with clay caps of varying lateral locations. We assume the hidden resource below the clay cap can only exist in one of $N$ discrete locations. Let us represent each model by

![Figure 3. Conceptual model of electrical resistivity for a hidden geothermal resource (from Cumming, 2009).](image-url)

![Figure 4. Decision tree where squares depict the spatial decision alternatives and the elliptical nodes depict the uncertainty of the clay cap locations and the resource existence. Lastly, the unique combination of these alternatives and uncertainties results in an outcome measured in value (diamond-shaped nodes).](image-url)
where vector \( z \) contains the electrical resistivity and any other relevant properties (i.e., temperature, porosity, etc.) of the model and the variable \( x \) identifies the location of the throat of the clay cap: our proxy drilling target (Figure 3). The \( x_i \) location represents the shallowest access to the potential resource. Within our prior models, the clay cap is represented at \( N = 15 \) different locations, where the horizontal location \( (x) \) of the throat varies between the lateral positions of \(-3500 \text{ m} \) and \(+3500 \text{ m} \). Figure 5 demonstrates model \( z(X = 0) \); the throat depths in all models are fixed from 1.1- to 1.5-km depth. The clay cap is 3 km wide.

As seen in equation 2, a model that does not include any clay cap at all is also included in our prior model space such that \( x_i = N + 1 \) represents the absence of any clay cap within the exploration area. Initially, we assume that the low electrical resistivity of the clay cap is equivalent to higher temperatures and higher permeability thanks to faults and fractures shown in Figure 2.

We assume that one can only consider drilling in these \( N \) locations, if at all. Thus, the spatial alternatives (represented by index \( a \) in Figure 4) consist of \( N \) possible clay cap locations where one may choose to drill or not. These are represented as the columns in Table 2 whereas the different possible clay cap locations (model categories \( x_i \)) are represented by the rows of Table 2. The last column of the table represents the option to not drill at all, and the last row in Table 2 represents the model with no clay cap. Table 2 displays a value outcome matrix that penalizes drilling decisions that miss the throat by \( \geq 1500 \text{ m} \); we will call these the harsher value outcomes. Alternatively, Table 3 is a more “lenient” value outcome matrix, in that losses are not incurred until the drilling location is farther (\( \geq 2000 \text{ m} \)) from the actual location of the throat. The individual values in Tables 2 and 3 are arbitrary and can be replaced by more realistic dollar amounts to represent specific locations or particular drilling applications. The values seen in Tables 2 and 3 should represent the revenue minus the costs expected for drilling at a particular location (represented by \( q_a \)) when the actual location of the resource is at location \( x_i \); thus, they decrease as you move away from the diagonal because the drilling location is farther from the resource.

Tables 2 and 3 represent the value outcome metric, which is a function of the decision alternative \( a \) and the throat location of \( x_i \). The value metric allows for comparison between outcomes from

![Figure 5. One realization of the electrical resistivity model representing the hidden resource. The dark gray cap represents the 10-ohm-m layer in Figure 3, depicted as light gray. The white layer is the air, and the 100-ohm-m background subsurface is light gray.](image)

\[ z(X = x_i), \quad i = 1, \ldots, N + 1, \quad (2) \]
different decision alternatives, which can be represented by function $g$:

$$v_a(x_i) = g_a(z(X = x_i)), a = 1; : : : ; N + 1;$$

$$i = 1; : : : ; N + 1;$$

(3)

Tables 2 and 3 demonstrate that the highest outcomes (most successful decisions) occur along the diagonals: where the drilling location aligns with the actual location of the throat. The value outcomes then drop off as you move away from the diagonal signifying the mismatch between the possible resource location and the drilling location.

$V_{prior}$: The best decision option given the prior uncertainty.

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 (missing the resource or drilling into an uneconomic reservoir). By using $V_{prior}$, a decision maker can logically determine when one should participate in this lottery given the prior uncertainties and possible gains and losses.

$V_{prior}$ is only dependent on the current state of uncertainty ($Pr(X = x_i)$) and the outcomes of the decision ($v_a(x_i)$) is given by

$$V_{prior} = \max_a \sum_{i=1}^{N+1} Pr(X = x_i) v_a(x_i), a = 1; : : : ; N + 1;$$

(4)

The $V_{prior}$ expression identifies which decision alternative will, on average, result with the highest value (most successful outcome). The prior distribution is used to calculate a weighted average inside the summation and the $\max_a$ finds the highest outcome value among all the different spatial alternatives $a$.

$V_{prior}$ is inherently a very subjective measure because the prior state of knowledge is characterized by an unknown probability distribution. Therefore, we test three different prior distributions and two different value outcome matrices (Tables 2 and 3) and how they affect the final VOI imperfect. Recall that the main purpose of this work is to include the effects of 2D geophysical inversion inaccuracies and non-uniqueness in a VOI assessment. We include several prior uncertainties and two possible profit/loss scenarios to demonstrate their role in the final VOI. We do not intend to perform a comprehensive analysis of the role of either of these in VOI as we assert these will be easier to define for specific exploration problems.

Figure 6 displays the three prior distributions. The uniform distribution (dashed line with squares) declares that there's an equal likelihood that the clay cap exists at any of the $N$ locations between $-3500$ and $+3500$ m. The two Gaussian distributions (with circle and diamond markers, respectively, in Figure 5) reflect a belief that the resource is centered at $x = 0$. The Gaussian with the smaller standard deviation (diamond markers) reflects less uncertainty of the location than the Gaussian with the larger standard deviation.

Table 3. Lenient value outcomes (expressed in thousands of dollars) that drop off quickly (i.e., losses are experienced when drilling $\geq 2000$ m from the actual throat). Rows represent the actual throat location and columns represent the drilling location (decision alternative). Same shading scheme as Table 2.
The value of spatial information

The positive VOI_{perfect} results indicate that a new source of information could have value. However, as indicated in Figure 1, once we consider a specific source of information and include its inaccuracies in locating the clay cap throat, the value of imperfect information (VOI_{imperfect}) will be less than VOI_{perfect}. For this demonstration, we want to assess the value of the MT geophysical technique. Consequently, we must have an estimate of MT’s reliability to locate the throat. We estimate the reliability by mimicking the data collection, inversion, and interpretation processes. Specifically, we simulate the physics of the MT measurement on many geothermal reservoir models that represent possible exploration scenarios, corrupt the data to simulate measurement error, and then perform inversions of noisy MT data. Lastly, we interpret from the resulting resistivity images the location of the throat.

Our goal is to assess how well an MT inversion can identify the ideal location for drilling a geothermal exploration well: at the throat of the clay cap. To do this, we identify the anomalous region of lower resistivity (the area of the clay cap), and then at several depth locations, we search for the high-resistivity locations that represent the throat. We do this for the multiple depth and noise realizations to get multiple interpretations. Multiple picks (from the realizations and depths) better represent the uncertainty one would expect when locating the clay cap throat from an inversion image and also increase the samples used that generate the statistics for the MT reliability. The workflow to estimate the value with imperfect MT information can be described in six steps:

**V_{perfect}**: Value with perfect information

The value of perfect information (VOI_{perfect}) provides an upper bound to the utility benefits that a given information source could offer, given the prior uncertainties and modeled value outcomes. Perfect information for this example assumes that some measurement could reveal without error, the location of the throat of the clay cap. Theoretically, one would drill exactly at the throat with this perfect information. The value with this perfect information is expressed as

\[ V_{\text{perfect}} = \sum_{i=1}^{N+1} \Pr(X = x_i) \left( \max_a \nu_a(x_i) \right), \]

\[ a = 1, \ldots, N + 1, \]

(5)

which crucial difference from \( V_{\text{prior}} \) is the placement of the \( \max_a \), which is now before the expectation operation: \( \sum_{i=1}^{N+1} \Pr(X = x_i) \).

Equation 5 suggests that we will have the information before we choose a location for drilling (\( a \)), and therefore, we can choose the alternative that has the highest value for each clay cap location. For both value outcome matrices (Tables 2 and 3), this is the weighted average value along the diagonal $\$450,000 = (1 - P_0) * $500,000 + $500,000 + P_0 * $0$. Then, the average of all best outcomes for each of the clay cap locations is calculated. Because all three of the prior distributions are symmetric, \( V_{\text{perfect}} \) is $\$450,000 for all six combinations of prior uncertainty distributions and value outcomes (Table 5). Following equation 1 (depicted graphically in Figure 1), the value of perfect information is the difference between this and \( V_{\text{prior}} \).

As seen in Table 5, information has the most value ($\$450,000) when the prior uncertainty is high (the uniform prior and wider Gaussian) along with harsher value outcomes. This is logical from the viewpoint of the decision maker.

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**METHODOLOGY: SIMULATING MAGNETOTELLURIC DATA COLLECTION, NOISE, INVERSION, AND INTERPRETATION OF CLAY CAP LOCATION**

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**Figure 6.** Three different prior distributions used to test \( V_{\text{prior}} \) sensitivity; \( V_{\text{prior}} \) only defined at discrete clay cap locations (every 500 m). The sum of each prior distribution: 1 - Pr (no clay cap).
1) The MT response for each prior model $z(x_i)$ is predicted using the electromagnetic simulation MARE2DEM (Key and Ovall, 2011). The forward response is represented by function $f(\cdot)$ and the data set for each prior model by $d_i$:

$$d_i = f(z(x_i)), \quad i = 1, \ldots, N + 1.$$  

Frequencies between 0.001 and 1000 Hz (21 frequencies total, 3–4 per decade) are observed at 21 receiver locations. The line of MT receivers covers $-5000$ to $+5000$ m. Therefore, for all $N$ locations, the entire clay cap is covered.

2) Four percent random Gaussian noise is added to all of the $N + 1$ MT forward responses (each of the prior models). Different seeds are used to generate different random noise. Different realizations of noise, indexed by $t$, are added to the same forward response. Therefore, $T \times (N + 1)$ noisy data sets are generated as

$$\tilde{d}_i^{(t)} = d_i + 0.04d_i \times N(0, 1), \quad i = 1, \ldots, N + 1,$$

$$t = 1, \ldots, T. \tag{7}$$

3) Geophysical least-squares inversions ($\tilde{f}^{-1}$) are performed using the $T \times (N + 1)$ noisy data set; $T = 5$ inverted electrical resistivity models ($\tilde{\rho}_i^{(t)}$) are obtained for every prior model. Figure 7 includes three prior models (left column), and their respective inversion models (right column) are given as

$$\tilde{\rho}_i^{(t)} = \tilde{f}^{-1} (\tilde{d}_i^{(t)}), \quad i = 1, \ldots, N + 1, \quad t = 1, \ldots, T. \tag{8}$$

Each inversion took an average 20 min on one node of an Intel Xeon X5660 (one node = 12 cores and 24 GB memory). All inversions use identical regularization schemes, with a horizontal to vertical smoothing factor of 3, that are based on minimum roughness to stabilize the inversion (Key and Ovall, 2011).

4) For each inversion result, we use an automatic interpretation algorithm (denoted by function $h(\cdot)$) to locate the lateral position of the clay cap throat at the true depth locations (indexed by $k$) that span the thickness of the 500-m clay cap throat. Therefore, for each inversion image, an interpretation of the lateral location of the throat is made at the following actual depths of the throat: $1.1, 1.2, 1.3, 1.4, 1.5$ km. Figure 8 shows the automatic picks at these depths for one example inversion image; these picks are represented by $x_j^{(t,k)}$ as

$$x_j^{(t,k)} = h(\tilde{\rho}_i^{(t)}), \quad i, j = 1, \ldots, N + 1, \quad t = 1, \ldots, T,$$

$$k = 1, \ldots, K. \tag{9}$$

In other words, there are $T \times K$ number of picks for each prior model $z(x_i)$; because these picks may not be at the same lateral location as the original model, $\tilde{x}_j$ is not necessarily equal to $x_i$. The lower resistivity region ($\rho < 10^{1.3}$ or 50 ohm-m; the darker colors of Figure 10) represents the clay cap or alteration. Therefore, the interpreted throat locations $\tilde{x}_j^{(t,k)}$ are the lateral locations of maximum resistivity (representing the apex of the isotherm) within this lower resistivity region that represents the clay cap. This interpretation algorithm allows for different lateral locations to be chosen at the five fixed depths given above. It is a significant assumption that the depths are known. Future work will improve this algorithm to allow for uncertainty in the depth interpretation.

5) The information posterior is calculated by determining the likelihood from comparing the inversion picks and their respective actual clay cap locations and then scaling this likelihood with the prior and marginal distributions. First, the number of picks are counted at each location bin $x_j$ (including the “no pick” outcomes) for every target (original) location $x_i$ (including the “no target” cases) as

$$c_{ij} = \sum_{t=1}^{T} \sum_{k=1}^{K} \delta(x_i - \tilde{x}_j), \quad i, j = 1, \ldots, N + 1, \tag{10}$$

where $\delta$ is 1 if pick $(t,k)$ is in bin $j$ and 0 otherwise. Next, these counts are scaled by the total number of possible picks that are possible for a target at $x_i$: $T \times K$ (number of realizations \times number of depth picks) as

Figure 7. First column contains three prior models. The second column represents their respective inversion results. Clay cap throat located at (a) $x = 0$, (b) $x = +2500$ m, and (c) $x = -2500$ m.
The value of spatial information

\[ Pr(\tilde{X} = \tilde{x}_j | X = x_i) = \frac{c_{ij}}{T \times K}. \]  

Figure 9 displays the likelihood/reliability calculated from the base case; this likelihood was generated assuming a uniform prior distribution. Finally, the posterior is calculated by multiplying the likelihood by the prior and scaling it by the adjusted marginal as

\[ Pr(X = x_i | \tilde{X} = \tilde{x}_j) = \frac{Pr(X = x_i) Pr(\tilde{X} = \tilde{x}_j | X = x_i)}{\sum_{i=1}^{N} \sum_{j=1}^{K} Pr(X = x_i) Pr(\tilde{X} = \tilde{x}_j | X = x_i)} \]

\[ = \frac{Pr(X = x_i) Pr(\tilde{X} = \tilde{x}_j | X = x_i)}{Pr(\tilde{X} = \tilde{x}_j)} \]

The posterior accounts for how frequently any interpretation is made. Figure 10a and 10b shows the posteriors calculated using equation 12 and the uniform and wide Gaussian (\(r = 1800\)-m) prior probabilities, respectively. The rows represent the actual or true clay cap location, and the columns represent the interpreted locations.

6) Last, the value with imperfect information (\(V_{\text{imperfect}}\)) is calculated using the information posterior as

\[ V_{\text{imperfect}} = \sum_{i=1}^{N} \sum_{j=1}^{K} Pr(X = x_i | \tilde{X} = \tilde{x}_j) \times \max_{a} \left\{ \sum_{i=1}^{N} Pr(X = x_i | \tilde{X} = \tilde{x}_j) \rho_a(x_i) \right\} \]

\[ a = 1, \ldots, N + 1. \]

The value with imperfect information \(V_{\text{imperfect}}\) (equation 13) uses the posterior as a “misinterpretation rate,” accounting for how frequently the interpretation of the MT images may correctly or incorrectly locate the clay cap. With this interpretation of the clay cap location \(\tilde{x}_k\) from the information, the alternative with the highest outcome can be selected (max in equation 13).

\[ \rho_a(x_i) = \begin{cases} 1 & \text{if } a = \text{true} \text{ clay cap location} \\ 0 & \text{otherwise} \end{cases} \]

\[ a = 1, \ldots, N + 1. \]

The throat is interpreted to be at lateral locations within the darker oval (\(\tilde{\rho} \leq 10^{-5}\)). This is calculated for every possible interpretation (index \(j\)) and these are weighted by the data marginal \(Pr(\tilde{X} = \tilde{x}_j)\).

Before continuing on to the VOI results that use the calculated \(V_{\text{imperfect}}\), an explanation should be made with respect to the reliability calculation. Similar to the value outcomes (Tables 2 and 3), the reliability (Figure 9) is binned into 500-m increments. Therefore, when a pick is made (e.g., an interpretation is assigned), this interpretation location \(x_j^{(i,k)}\) must be rounded to the nearest 500 m. Therefore, if a pick is 200 m away from the true throat location, it will be deemed correct, whereas at 300 m, it will not. We compared the statistics of these mismatches for a test batch of inversions using \(T = 15\) noise realizations for \(z(x_j = 0)\) versus \(T = 5\) for \(z(x_j = 0)\). They were deemed comparable because the mean and variance of the mismatches between the interpretations and true locations were similar. Although 15 realizations may produce different picks than only 5, this resolution is lost when the interpretations are binned into the 500-m increments.

With this in mind, the two information posteriors, shown in Figure 10, are reasonable; Figure 10a demonstrates the posterior

**Figure 8.** Example of interpreted lateral position (picks) at set depths = \(\{1.1, 1.2, 1.3, 1.4, 1.5\}\) km. The throat is interpreted to be at lateral locations within the darker oval (\(\tilde{\rho} \leq 10^{-5}\)). Picks are made within this darker oval at lateral locations with higher electrical resistivity. The example shown here is for when the true clay cap throat is between -500 and 0 m. Notice the grayscale limits are different from previous figures to better show the electrical resistivity.
assuming the uniform prior, and Figure 10b assumes the wide Gaussian. All interpretations are within three bins of the true throat location. This makes sense because the pick will only occur within the lower resistivity target (the clay cap), which is 3 km wide (six bins). In this example, the inversion and interpretation of the MT data indicate that none of clay cap throat locations will always be correctly located; this is indicated by the absence of 100% in the diagonal. The wide Gaussian prior distribution deems that throats at \( x = \pm 3500 \) m are less likely, and therefore, it has fewer “no picks” for these categories compared to the uniform prior. Thus, this is the largest difference between the two posteriors: the farthest right column of Figure 10a and 10b. This will influence the final VOI imperfect discussed in the next section.

The two VOI imperfect measures calculated using the two value outcome matrices (Tables 2 and 3) and the posterior of Figure 10a are $303,000 and $363,000, respectively. As expected (see the conceptual graphic in Figure 1), both of these VOI imperfect’s are lower than V perfect of $450,000 (equation 5). Also, VOI imperfect is lower when the harsher value outcome matrix (Table 2) is used. When the interpreted location does not match the actual location, this matrix will create larger losses and consequently a lower VOI imperfect compared to the case when Table 3 is used.

RESULTS: VALUE OF IMPERFECT INFORMATION

Now, the value with imperfect information \( V_{\text{imperfect}} \) can be put into the VOI equation (equation 1) to calculate the value of imperfect information \( \text{VOI}_{\text{imperfect}} \) as

\[
\text{VOI}_{\text{imperfect}} = V_{\text{imperfect}} - V_{\text{prior}}
\]

Six different VOI imperfect’s are calculated using the previous \( V_{\text{prior}} \)’s (Table 4) and the two \( V_{\text{imperfect}} \)’s. These are shown in part (a) of Table 6. The value of imperfect information is highest ($390,000) when the prior uncertainty of the clay cap location is the wide Gaussian (\( \sigma = 1800 \) m), and the penalties for drilling far from the clay cap are more lenient (Table 3). Information from MT should have more value when our ignorance is highest and the risk for costly outcomes from decisions is greater. However, the value of imperfect information (VOI imperfect) is lowest ($204,000) when the \( V_{\text{prior}} \) is greatest (Gaussian with \( \sigma = 900 \) m), and the lenient outcome values are used. As seen in Table 6a, this is explained by \( V_{\text{imperfect}} \) being higher for the lenient outcomes: misinterpretations are punished less using this value matrix.

Figure 10. Information posteriors for models with clay caps at 15 locations assuming (a) a uniform and (b) wide Gaussian prior distribution. Each row represents actual or true clay cap throats (prior model) and the columns represent how frequently that inverted throat was interpreted at different locations (represented by the symbol \( \sim x \)). Each column sums to 100%.

<table>
<thead>
<tr>
<th>Prior distribution ↓</th>
<th>( v_a(x_i) ): Harsh values (Figure 7)</th>
<th>( v_a(x_i) ): Lenient values (Figure 8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uniform prior</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 1800 ) m)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 900 ) m)</td>
<td>49,000</td>
<td>214,000</td>
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</tbody>
</table>

Table 4. \( V_{\text{prior}} \) for different prior uncertainties (rows) and different individual value outcomes (all values in $).
Additionally, Figure 10a and 10b demonstrates how the posterior of the narrow Gaussian results in fewer “no pick” interpretations when clay caps exist. Thus, the narrow Gaussian forecasts that fewer opportunities would be lost with these false interpretations of “no cap,” than when assuming a uniform prior.

Adding complexity to the prior models: The conductive, inactive sinter

We repeat the workflow described in the “Methodology” section, but we add some complexity to the prior models. Figure 11 depicts an inactive sinter above and to the east of the clay cap (the darker, more conductive feature). Sinters are a siliceous or calcareous deposit precipitated from mineral springs, and in Figure 3 (Cumming, 2009), it is hypothesized to have a lower resistivity (5 ohm-m) than that of the clay cap (10 ohm-m).

The sinter will impact the inversions and more importantly the interpretation of where the throat of the clay cap is. Figure 12 is the inversion result of Figure 11. We see that the MT image indicates the presence of the low-resistivity sinter but does not perfectly resolve its location. If we compare it with the inversion result without the sinter (Figure 7), we see that the area of lower resistivity (darker colors) has now shifted to the east (right) due to the sinters’ location.

MT inversions and interpretations are performed for models including a sinter at all \( v \) values in $). We see a visible shift from the diagonal to the east (right). Recall how the automatic interpretations are made: the location of the maximum resistivity is chosen from within the minimum resistivity region (representing the clay cap or alteration). Therefore, because the lower resistivity region (the darker area) has shifted east (right), the interpreted throat location has now shifted east (right). The other significant difference is seen in the column of interpreted location \( \gamma_j = -3500 \) m. This column indicates that none of the interpretations resulted in a throat at \( \gamma_j = -3500 \) m. This will be reflected in the data marginal: \( \Pr(\gamma_j = -3500 \) m) = 0.

The \( V_{\text{imperfect}} \) (equation 13) is calculated using this information posterior from the models with sinters and the two value outcome matrices. These are shown in Table 6. The \( V_{\text{imperfect}} \) has decreased for both value outcomes (columns of Table 6) compared to the cases

![Figure 11. One realization of the electrical resistivity model representing the hidden resource (dark gray, 10-ohm-m clay cap) with a sinter (represented in black, 5 ohm-m).](image)

<table>
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<tr>
<th>Table 5. ( V_{\text{imperfect}} ) for different prior uncertainties (rows) and different individual value outcomes (all values in $).</th>
</tr>
</thead>
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<tr>
<td>Uniform prior</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 1800 ) m)</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 900 ) m)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 6. ( V_{\text{imperfect}} ) results for models with (a) clay caps only, (b) with sinters, and (c) with sinters and gradually deeper to the east (all values in $).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models</td>
</tr>
<tr>
<td>(a) Clay cap only</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 1800 ) m)</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 900 ) m)</td>
</tr>
<tr>
<td>(b) Sinters</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 1800 ) m)</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 900 ) m)</td>
</tr>
<tr>
<td>(c) Sinters deepening to the east</td>
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<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 1800 ) m)</td>
</tr>
<tr>
<td>Gaussian prior (( \mu = 0 ) m, ( \sigma = 900 ) m)</td>
</tr>
</tbody>
</table>
where only the clay cap was modeled (Table 6a). This is what one would expect given the visible shift in the information posterior (assuming uniform prior) that includes the effect of the sinter (Figure 12). The subsequent VOI imperfect for the different V prior is also shown in Table 6b.

Deeper targets: Dipping eastward clay cap

Suppose that the prior geologic information postulates that if a clay cap exists in the eastern part of the considered location, it will be deeper than if it is in the extreme west. This could be due to many different geologic scenarios, such as local variations in mineralogy that cause the fractures to plug fractures more in the east than in the west, causing the clay cap to form deeper. Or perhaps the uplift regime would give reason to expect shallower clay caps to develop in the west. Figure 14 graphically demonstrates how the clay cap will be incrementally deeper with increasing eastern location. In our example, the clay cap and sinter are placed 100 m deeper every 500 m to the east. The fixed depths at which we locate the throat are shifted accordingly for each model and are still assumed known.

At $x = -2500$ m, the model is 200 m deeper than its original location, and at $x = +2500$ m, the model is 1200 m deeper than its original location. The top row of Figure 15 shows the inversion results for the clay cap and sinters of these two lateral locations at their original depths. The second row shows the inversion results for these same lateral locations but for the two increased depths. Even for $-2500$ m (only 200 m deeper), we see that the MT-inverted image does not recover electrical resistivities lower than 10 ohm m. The second column shows that the 1200 m deeper clay cap and sinter is not resolved at all.

In fact, the automatic interpretation does not identify any area of lower resistivity for clay caps at $x_i > +2500$. Therefore, these models only produce “no picks.” Figure 16 illustrates the information posterior (assuming uniform prior) for these dipping clay cap and sinters, where the largest difference in this information posterior relative to the two others is seen in the three most eastern and deepest clay caps ($x_i = (+2500$ m; $+3000$ m; $3500$ m$)$). This is a result of the inability of the MT technique to resolve the three deepest clay caps. Additionally, there appears to be some bimodal features of the information for all clay cap locations at $x > -1000$ m. These are the deepening clay caps, and thus, the automatic interpretation technique is placing the picks at the western and eastern boundaries of the lower resistivity body.

Table 6c contains the VOI imperfect results for the models with clay cap and sinters with varying depths. These VOI imperfect values are much less than the previous values (Table 6a and 6b).

Accounting for no resource under clay cap

Up until now, we have made a very significant assumption that a resource does exist under the clay cap: $\Pr(\theta = \theta_{k+1}) = 1$. Now, we will account for the probability of no resource existing under the clay cap. This is represented as the second uncertainty in the

<table>
<thead>
<tr>
<th>$x = -2500$</th>
<th>$x = -3000$</th>
<th>$x = -2500$</th>
<th>$x = -1500$</th>
<th>$x = -1000$</th>
<th>$x = 0$</th>
<th>$x = 500$</th>
<th>$x = 1000$</th>
<th>$x = 1500$</th>
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<th>$x = 3500$</th>
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<td>0.0%</td>
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<td>$\theta_{k+5}$</td>
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Figure 12. One inversion result from model shown in Figure 11 which includes a sinter. Outline of true locations of clay cap and sinter in black.
decision tree of Figure 4. We link each combination of prior model and decision alternative to two possible value outcomes: the value outcome if there is a resource ($\theta_{k-1}$) or not ($\theta_{k=0}$). The average of the two now replaces the quantity of equation 3 as

\[ v_a^{(i)}(x_i) = \Pr(\Theta = \theta_{k=0}) v_a^{(i)}(\theta_{k=0}) + \Pr(\Theta = \theta_{k-1}) v_a^{(i)}(\theta_{k-1}), \]

\[ a = 1, \ldots, N + 1, \quad i = 1, \ldots, N, \quad (15) \]

where $\Pr(\Theta = \theta_{k=0})$ is the probability of an economic resource existing under the clay cap, and $v_a^{(i)}(\theta_{k-1})$ is the outcome when one drills $(a = 1, \ldots, N)$ or not $(a = N + 1)$ when no resource is under the clay cap. We assume that the resistivity structure would remain the same whether a resource exists or not under the clay cap because the clay cap is representative of the historical temperature (see the Introduction). Table 7 demonstrates how the VOI decreases with decreasing probability of occurrence of an economic resource. Once the probability of resource is 50%, all VOI$_{imperfect} = 0$. The results in Table 7 assume the harsher value outcomes (Table 2) and $v_a^{(i)}(\theta_{k=1}) = -$500,000 for all drilling alternatives $(a = 1, \ldots, N)$ and $v_a^{(i)}(\theta_{k=1}) = 0$ when no drilling is performed.

![Figure 15. Inversion results for $x = -2500$ m (first column) and $x = +2500$ m (second column). The first row shows inversions where the clay cap and throats are located at their original depths of 500–1000 m. The bottom row shows inversions where the clay caps are located at 200 and 1200 m deeper, respectively.](image)

![Figure 16. Information posterior for models dipping with eastern lateral location of the clay cap and sinter.](image)

Table 7. VOI$_{imperfect}$ for different probabilities of an economic resource occurring under the clay cap.

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</table>

DISCUSSION

Our results show how the VOI depends on four factors. We identify these factors and discuss the limitations of each was presented in this work.

Table 7. VOI$_{imperfect}$ for different probabilities of an economic resource occurring under the clay cap.

<table>
<thead>
<tr>
<th>$x$</th>
<th>Pr($\theta = \theta_{k-1}$) = 1.0</th>
<th>Pr($\theta = \theta_{k-1}$) = 0.7</th>
<th>Pr($\theta = \theta_{k-1}$) = 0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Uniform prior</strong></td>
<td>$303,250 - 0 = 303,250$</td>
<td>$88,000 - 0 = 88,000$</td>
<td>$0 - 0 = 0$</td>
</tr>
<tr>
<td><strong>Gaussian prior ($\mu = 0$ m, $\sigma = 1800$ m)</strong></td>
<td>$338,000 - 0 = 338,000$</td>
<td>$105,000 - 0 = 105,000$</td>
<td>$0 - 0 = 0$</td>
</tr>
<tr>
<td><strong>Gaussian prior ($\mu = 0$ m, $\sigma = 900$ m)</strong></td>
<td>$384,000 - 49,000 = 335,000$</td>
<td>$134,000 - 0 = 134,000$</td>
<td>$0 - 0 = 0$</td>
</tr>
</tbody>
</table>
The reliability of the information from magnetotelluric: data, inversion, and interpretation

Table 6 contains VOI_{imperfect} quantities that demonstrate the impact of the “imperfect MT images.” Because of inaccuracies introduced from the added noise, inversion, interpretation, and MT’s limited resolution, we will not always perfectly identify the throat’s location. We account for this by estimating MT’s reliability (and in turn the information posterior) and calculating the value of imperfect information (VOI_{imperfect}). First, the inversion technique uses a regularization scheme based on minimum roughness to stabilize the inversion. This approach produces smooth images where the structural features are smeared and accurate shape information is lost. Second, MT’s ability to resolve the throat of the clay cap was diminished when a conductor of 5 ohm-m (representing a possible sinter) was included. Third, the information posterior reflected increased inaccuracy when the depth of the structure (clay cap) was increased incrementally. This is consistent with the loss of resolution with depth that is observed with all surface-based geophysical surveys.

The VOI results are dependent on the automatic interpretation that was used to identify the clay throat location in every inversion (described in the “Methodology” section). Interpretations are usually made by professionals with expertise in the technique and the particular location being imaged. Modifications could and should be made for specific applications.

We remind our readers that the objective of the study is to develop and demonstrate a VOI method that can evaluate spatial information from geophysical techniques, including the effects of 2D inversion. We chose to add complexity (sinter and increasing depths) to demonstrate the ability of the VOI methodology to incorporate geophysical limitations, including nonuniqueness and lack of sensitivity and resolution. When a sinter was added to the east of all clay caps, this introduced a slight bias to interpret the location of the throat to the east of the actual location. Ability to discern any throat location was lost when the clay cap reached a depth 1200 m deeper than the original depth. For real applications, and an economic geothermal reservoir

The description of the prior uncertainty

Table 4 summarizes the three different V_{prior}’s calculated to demonstrate the role of V_{prior} in the VOI assessment. It intuitively makes sense that with greater prior uncertainty (i.e., the uniform distribution), a new source of information such as electrical resistivity images computed from MT data will have more potential to provide value to decision makers because the V_{prior} is lower (Figure 1). However, the prior also influences the posterior by predicting how often an interpretation might be made (the marginal). Table 6 demonstrates that the wide Gaussian has the highest VOI_{imperfect} for all model complexity scenarios (a), (b), and (c). This is due to fewer “no pick” interpretations when a clay cap exists and because V_{prior} = 0. The V_{imperfect} for the narrow Gaussian was highest for all three cases, but the nonzero V_{prior} ($49,000) reduced the VOI_{imperfect}. Sato (2011) summarizes some of the counterintuitive aspects of VOI, one being that VOI does not necessarily increase as the prior uncertainty increases (Gould, 1974). Our intent when evaluating three possible prior uncertainty models (Figure 6) was to provide the reader with some intuition about the VOI metric. However, we do not claim nor was it our intent to provide a comprehensive study of the relationship of the prior uncertainty and VOI.

The value outcomes (Tables 2 and 3)

The value outcomes represent the estimated gains and losses due to the combination of the true location of the clay cap and the choice of drilling location. The value outcomes of Table 2 penalize drilling decisions that are ≥1500 m from the actual throat (harsh value outcomes). In this situation, the value of perfect information will have more value when using this value outcome matrix versus that of Table 3 because it can help us avoid costly outcomes. This is seen in Table 5. However, once the fallibility of the MT inversions is considered, V_{imperfect} will reflect the higher penalties for misinterpretations using the harsh value outcomes.

We have made an important assumption that the decision maker is risk-neutral (not risk-adverse or risk-prone), thus assuming that the decision maker’s utility function is linear and the cash equivalent is equal to the expected value (Pratt et al., 1995; Bratvold et al., 2009). More complicated risk attitudes and preferences for certain decision alternatives could be incorporated. Again, this is outside the scope of our study.

The strength of the relationship between a clay cap and an economic geothermal reservoir

Fundamental to the VOI paradigm is that the information source must be sensitive to the parameter that affects the outcome of the decision. The last set of results varied the probability of clay cap presence being correlated with the existence of an economic geothermal resource. Once the probability of a resource existing below a clay cap drops to 50% (thus smaller chance of a high-valued outcome), the VOI = 0 (Table 7). Here, we focus on hidden resources and assume that a clay cap is indicative of a possible geothermal source. Many more geothermal possibilities could be included, such as a low-enthalpy system, in which there would be no clay cap.
Possible applications to current oil topics

Lastly, we like to remind readers of the broader topics to which this methodology is applicable. An area where VOI could be useful is determining if ocean-bottom nodes provide significantly improved efficacy versus the conventional 3D seismic survey. By evaluating the VOI of each, decision makers could justify (or not) the significant cost increase for using ocean-bottom nodes.

CONCLUSIONS

VOI quantifies how relevant and reliable any particular information source is, given a decision with an uncertain outcome. VOI decreases as the efficacy of the MT technique to accurately delineate the correct lateral location of the throat of the clay cap decreases (captured in various information postiors). We have demonstrated this by adding additional complexity and deepening the targets in the earth models. Secondly, the prior uncertainty has the ability to either increase or decrease the final VOI assessment. Lastly, VOI is tightly correlated to the relationship between the property measured by the information and the decision variable. When the presence of a conductive clay cap was no longer considered to ensure the presence of an economic reservoir, VOI decreased as this relationship declined.

VOI is a powerful technique that can be used to justify the costs of collecting the new, proposed data. We have provided a flexible framework that includes the spatial uncertainty in the decision and the information itself, and demonstrated how one may test the sensitivity of the final VOI to reliability of the information, prior uncertainty, and the magnitude of profits or losses. This methodology can be applied to multiple subsurface resource decisions and geo-physical techniques to assess the possible gain of knowledge.

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