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Analysis and Evaluation of Geothermal Systems using Efficacy of Information and Loss Functions

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ABSTRACT

In the early prospection and exploration phases of geothermal systems, uncertainty of fundamental reservoir parameters, such as presence, depth or permeability magnitude, is typically high, due to often moderate geological data availability. Decisions regarding specific exploration measures, such as 2D or 3D seismic surveys or the drilling of exploratory wells, are therefore connected to certain risks, as it is unknown whether a chosen measure will yield a desired positive information gain and thus whether the funds for these exploration measures were invested without return. We apply methods from information and decision theory to geothermal exploration scenarios to estimate the value of information of certain exploration measures and quantify influence of associated structural uncertainties on estimated monetary losses (negative EMV) using loss functions.

Based on a case study in North Rhine-Westphalia, Germany, we present two methods that illuminate different aspects of decision-making for exploration measures. Firstly, we apply the method of Efficacy of Information on an ensemble of equally likely reservoir model realizations to test the change of EOI of different drilling locations for planned exploratory wells. At one drilling location, we exercise application of loss functions to assess the financial impact of over- or underestimating drilling depth to reach the reservoir bottom. We establish loss functions for drilling depths to a geothermal reservoir and analyse the effects of over- or underestimating these parameters on drilling costs.

1. INTRODUCTION

Especially in the recent three years, exploration for geothermal resources has accelerated in many European countries. In addition to emerging crises on the continent, the pressing challenge of climate change necessitates a shift towards sustainable, renewable base-load energy sources, especially for the heating sector. Compared to exploration in the oil and gas sector, exploration and development of geothermal systems face higher risk, as the financial yield of a successful well does usually not compensate for a small number of dry wells. In the light of high uncertainty in many regions currently explored for geothermal energy sources, decisions as to which exploration measure should be conducted where, are crucial. Further, there is usually the need to encapsulate ranges of uncertainty into discrete numbers for decision makers to arrive at a decision whether an exploration activity should be pursued or not. In this paper, we present two supporting approaches for decision making in an exploration scenario at Weisweiler, located in western Germany between Aachen and Cologne (Jüstel et al., 2025). The two presented methods for support decision making in exploration, analysis and evaluation of geothermal systems are: Efficacy of Information (Caers et al., 2022) and loss functions (Berger, 1995). These methods will be explained in a bit more detail in the following, but in a nutshell: efficacy of information is a model-based approach to estimate how much an activity can reduce uncertainty in a part of a model. Loss functions are a tool to estimate the expected loss of an informed decision in light of uncertain parameters.

2. METHODOLOGY

In the following, we briefly describe two key methods, which are used in this work: Efficacy of Information and loss functions. As both approaches have to be seen in a Bayesian context, we also provide a short recap of Bayesian inference.

2.1 Efficacy of Information

In decision theory, the Value of Information (VOI) is a metric for evaluating how information affects decisions under uncertainty (Hall et al., 2022). It quantifies, how much – in terms of a currency value – new information can reduce financial risk of a project, i.e. how said information can impact on decision making. Another term, coined by Caers et al. (2022) is Efficacy of Information (EOI). Unlike VOI, EOI has no financial dimension, but refers to a metric which quantifies by how much future information can, on average, reduce uncertainty of an expected value of a parameter, e.g. how much can an exploration borehole at location (x,y) reduce uncertainty about depth and presence of a potential geothermal reservoir. EOI is particularly useful in scenarios with uncertain economic models. Essentially, EOI is the difference between expected values of a certain outcome, e.g. drilling depth or reservoir presence, before and after acquiring new information:

$$EOI = e_{post} - e_{prior} \qquad [1]$$

The methodological approach and calculation of expected values, especially e_{post} is presented in Caers et al. (2022). How EOI can be extended to Value of Information has been well described in Hall et al. (2022).

2.2 Loss functions

In project development with an uncertain yield, miscalculations or erroneous estimations of a target value will come at a certain financial loss. For instance, a mismatch between expected and true heat in place (HIP) of a geothermal reservoir system will come at a certain financial loss (Figure 1).

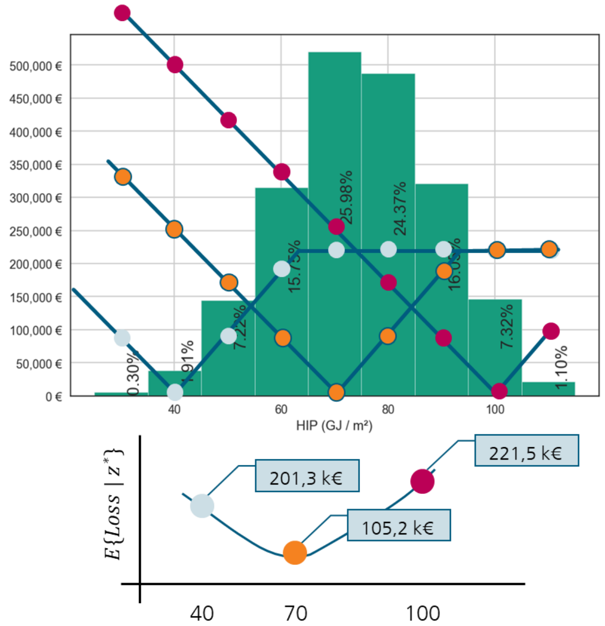

Figure 1: Example of calculating the expected loss (eq. 3) over a discretized approximation of uncertain HIP, for three different estimates (grey = 40 GJ/m², orange = 70 GJ/m², red = 100 GJ/m²) using the same loss function.

The aim of using loss functions is to minimize the expected loss resulting from these misestimations, which are unavoidable when considering uncertain parameters. Loss functions are a classical tool in Bayesian risk analysis, where they are modelled through the probability distribution of uncertain parameters (Berger, 1985). Loss functions (L) are defined by the difference between an actual parameter value (θ) and the estimated parameter ($\hat{\theta}$). The accuracy of the parameter estimate ($\hat{\theta}$) decreases with increasing loss (Berger, 1985; Davidson-Pilon, 2015). The fundamental forms of loss functions are the absolute loss function (L1 loss) [2] and the quadratic loss function (L2 loss) [3], where smaller misestimations in the absolute loss function and larger misestimations in the quadratic loss function are weighted more heavily.

$$L(\theta, \hat{\theta}) = |\theta - \hat{\theta}| \qquad [2]$$

$$L(\theta, \hat{\theta}) = (\theta - \hat{\theta})^2 \qquad [3]$$

The estimated parameters can be either overestimated or underestimated, with symmetrical loss functions treating the residuals equally (Hennig & Kutlukaya, 2007). Usually, however, over- or underestimations have different impacts, yielding asymmetric loss functions (Weber, 1994), as shown in Figure x. Some examples of asymmetric loss functions include the LINEX loss function, the Huber loss function, or custom loss functions (Huber, 1964; Stamm et al., 2019; Varian, 1975).

Further, in most practical applications, the true parameter value is also unknown, which is why the expected loss is calculated as a function over the entire probability distribution (Davidson-Pilon, 2015). With a discrete approximation, the expected loss can be calculated by multiplying the difference between each histogram class and the estimated value with the corresponding probabilities and creating the sum:

$$E\{Loss|\hat{\theta}\} = \sum L(\theta - \hat{\theta})\, p(\theta) \ [4]$$

2.3 Bayesian inference

A central aspect in a Bayesian context is the update of beliefs, i.e. the probability of a hypothesis, when provided new information. Essentially, this update can be expressed as the combination of prior knowledge (prior probability) with new data (likelihood) yielding an updated probability of the hypothesis (posterior probability):

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} \qquad [5]$$

Both described methodologies, EOI and loss functions work within a Bayesian framework. For EOI, the update of uncertainties and inherently also probabilities by acquisition of new information is a prime example of applying Bayes rule (equation [5]). EOI is evaluated by how significantly it updates the probability of the hypothesis, i.e. how it influences the posterior. Loss functions in a Bayesian context also depend on the update of ones beliefs, as this is expressed by a change of the uncertainty distribution (prior → posterior). The estimation of expected loss can be set in relation to the expected cost of acquiring new information, which is how Bayesian inference weaves in decision theory.

3. GEOLOGICAL BACKGROUND AND MODEL

The area of the case study, the Northern Eifel and its foreland are in the external part of the Rhenohercynian Zone of the continental European Variscides (Kossmat 1927; Schulmann et al. 2022). The associated foreland to the NW of the Rhenish Massif comprises the SW–NE striking Aachen Foreland Fold-and- Thrust Belt and the Variscan Deformation Front, overlain by the youngest outcropping thrust, the Aachen Thrust (Drozdzewski et al. 1994, 2009). Shortening was localised on the Fold-and-Thrust belt (Inde Syncline/Synclinorium) and the adjacent synclinal structure (Wurm Syncline; Wrede et al. 1993) forming an array of imbricate thrusts (Butler & Bond 2020). The Palaeozoic strata of the Northern Eifel and its foreland consist of Cambrian and Ordovician metamorphic rocks cropping out in the Stavelot-Venn Massif and of Lower Devonian to Lower Carboniferous siliciclastic and calcareous rocks of the Rhenohercynian Basin (Ziegler 1990; Franke 1995, 2000). This succession includes the Dinantian (Lower Carboniferous) platform carbonates deposited around the Brabant Massif and in isolated platforms in Belgium, the Netherlands, and Germany (Bless et al. 1980) and the Middle to Upper Devonian Massenkalk reef carbonates (Krebs 1974). These two stratigraphic units in combination with fractured sandstones of the Upper Devonian Condroz Group comprise already three promising reservoirs for geothermal exploration (e.g. Reith 2018; Arndt et al. 2021; Balcewicz et al. 2021; Fritschle et al. 2021; Lippert et al. 2022). Due to the very low matrix porosities (< 5%) and permeabilities (< 10 mD; e.g. Balcewicz et al. 2021; Lippert et al. 2022; for the Devonian carbonates), working hydrothermal systems rely on fractured, faulted and/or karstified (epigenic and hypogenic) carbonates (Mijnlieff 2020). For the Devonian Condroz Group sandstones, permeability also relies on fractures and permeable faults (Mijnlieff 2020).

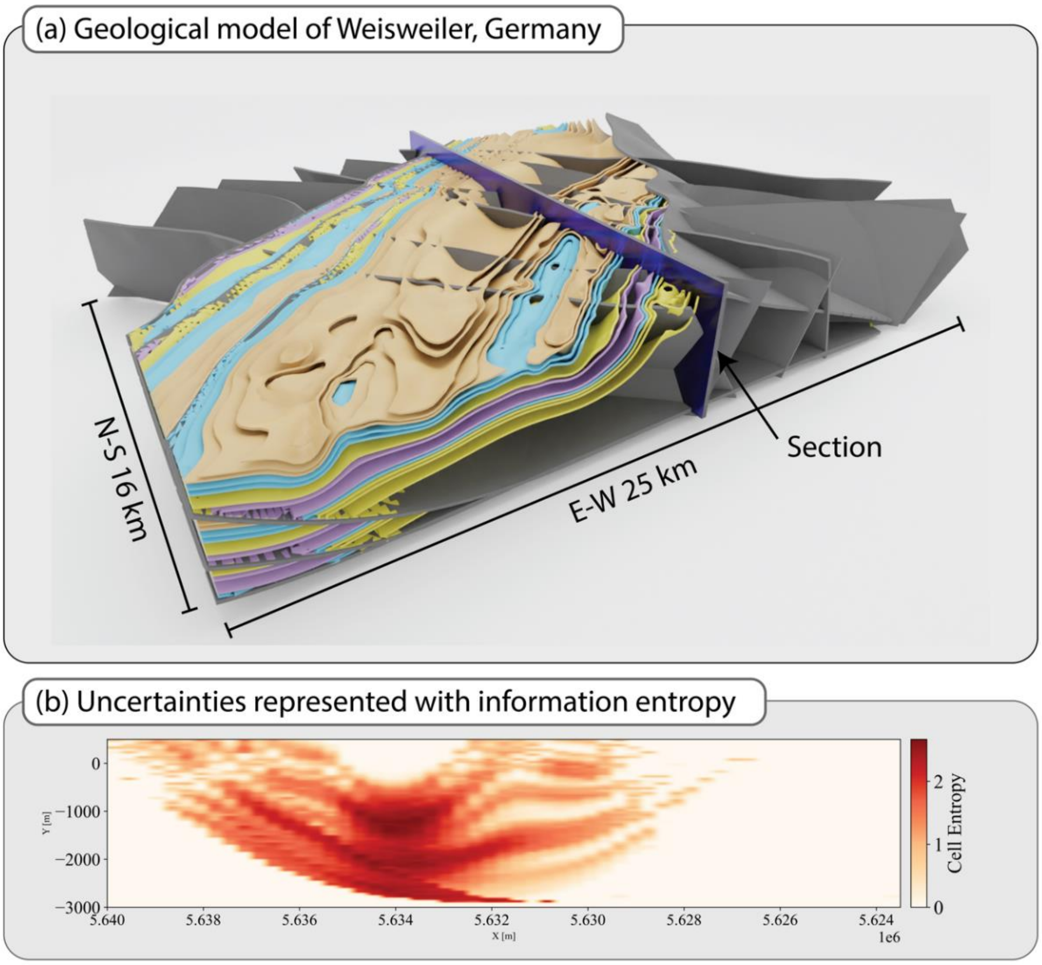

Figure 2: (a) Blender rendering of the structural geological model after Jüstel (2025); (b) Information entropy on a NW-SE cross section through the model (Jüstel et al., 2025). Figure adapted from Wellmann et al. (2024).

Available data and knowledge about the region were used to create an ensemble of 3D structural geological models in a probabilistic approach, with focus on the spatial distribution and depth uncertainties of major lithological units, among others the Carboniferous and Devonian carbonates. The ensemble comprises a set of 100 equally likely realizations and serves as a prior distribution for applying methods presented in chapter 2. Figure 2 shows a 3D rendering of the model and a cross section striking NW-SE through the centre of the models. The uncertainty of the model ensemble is depicted as Information Entropy (IE) (Shannon 1948; Wellmann

& Regenauer-Lieb, 2012), which is a combined measure for uncertainty and potential information gain. For this paper, we apply EOI and loss function to the 2D cross section in Figure 2, as extension to 3D makes EOI calculation much more expensive. The model ensemble consists of 100 realizations, each comprising 3850 cells.

4. RESULTS

4.1 Efficacy of information

Basis for calculating Efficacy of information is the model ensemble comprising 100 realizations. EOI is calculated on a 2D section perpendicular to the main thrust systems in the region. Target for assessing a suited location for a potential exploration well with the drilling target being the Dinantian carbonates (see section 3). As we focus on these carbonates for the EOI study, we reduced the parametric dimension of the ensemble to 2 in each realization:

- 1 where the model realization shows Dinantian carbonates
- 0 everywhere else

To briefly summarise the calculation of EOI based on this ensemble: via a PCA, we first calculated the eigenvalues and eigenvectors of the realizations. These are used to estimate the covariance of a prior distribution of reservoir depth, to create new realizations, which, however, are conditioned to occurrences of Dinantian carbonates in simulated boreholes. In a nutshell, for each realization, simulated boreholes (red line in Figure 3) are the depth values of Dinantian carbonates (yellow cells in Figure 3) at each horizontal grid node. For instance, a simulated borehole at the red line in Figure 3, would show many zeros where no Dinantian carbonates would be encountered and ones, where Dinantian carbonates would be encountered at deeper parts of the well.

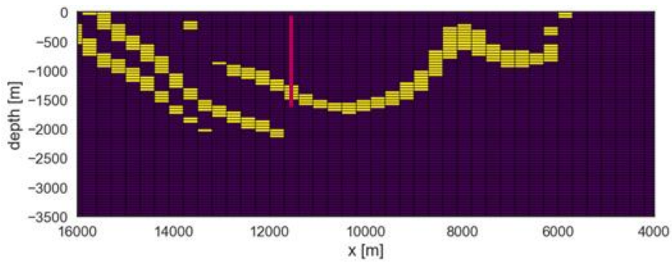

Figure 3: Example of extracting simulated borehole values from a realization.

As stated, for each simulated borehole new realizations are calculated, which are now conditioned to the findings in the respective borehole. This is called the pre-posterior, providing us an updated mean and variance, which can be used to update the 2D realizations using the eigenvalues and eigenvectors assessed by the PCA in the beginning. This yields e_{post}, while e_{prior} are the expected occurrences of Dinantian carbonates in the original model ensemble.

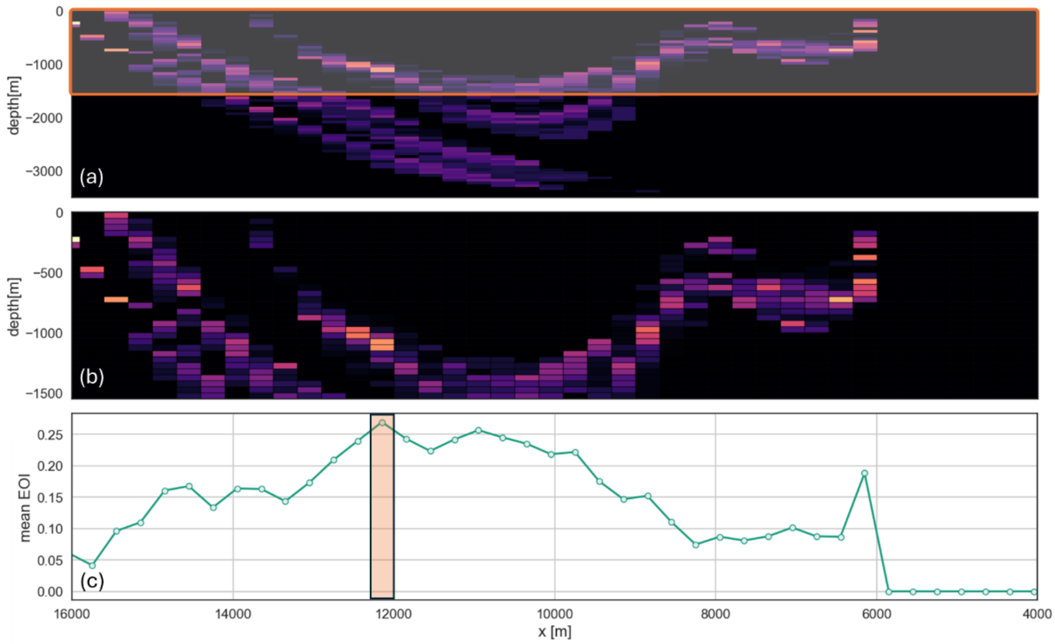

Figure 3: (a) Average EOI of the 2D model ensemble. Black indicates zero EOI, brightness of cells correlates with EOI value; (b) Zoom-in on the first 1500 meter of the average EOI; (c) mean EOI values for each grid column over the whole model depth range. The maximum EOI is at x index 40.

Figure 3 shows the average EOI of all pre-posterior realization. Due to the importance of thrusts in the geological model, the overall tectonics and shape of the Dinantian carbonates are still visible in this ensemble, as thrusts work like a cut-off on the vertical uncertainties of the respective geological unit. Higher EOI values indicate that in these cells, the impact on reduction of overall uncertainty is highest. However, a potential exploration borehole can be understood as an integration over depth, i.e. it does not only gather information at a specific depth, but over its whole depth. Assuming a 3 km deep exploration borehole, the best location according to EOI is not, where the single highest EOI values (brightest cells) are, but rather where the average EOI over depth is highest (Figure 3, (c)). Here, that's the case at the northern flank of the main syncline in the model. We choose this location for a subsequent assessment of how loss functions can be applied to the parameter drilling depth, as the specific depths of the Dinantian carbonates is still uncertain.

4.2 Loss functions

EOI assessment provided a general hint as to where information from exploration drilling might yield the most significant reduction of uncertainty. As an example for assessing the influence on uncertain reservoir depth on drilling costs, we apply loss functions for under- and overestimating the drilling depths to reach the shallowest stack of Dinantian carbonates at the designated drilling locations (i.e. the cells at location x=40 in Figure 3 (b)). Due to the stacking of the carbonates due to thrusting, assessment for the whole depth range is more complicated, as this represents a multimodal distribution for depth uncertainty.

Under- or overestimation of drilling depth to a geothermal reservoir have different impacts on the expected losses. Significantly underestimating drilling depth would mean a potential lack of drill pipes, drilling fluid, etc. in planning, and materials might have to be backordered on short notice. In the worst case, drilling operation may stop for a short period of time. Overestimating drilling depth, on the other hand, comes with different costs, e.g. allocating too many funds for material. Figure 4 (a) shows a loss function for drilling depth. Here, L1 loss functions (equation [2]) were chosen with a slightly assymmetric slope. Underestimation has a higher slope, thus punishing significant underestimations of drilling depth more than overestimations. In addition to differences in under- and overestimations, we added risk-affinity factors ranging from 0.5 (risk averse) to 1.5 (risk affine).

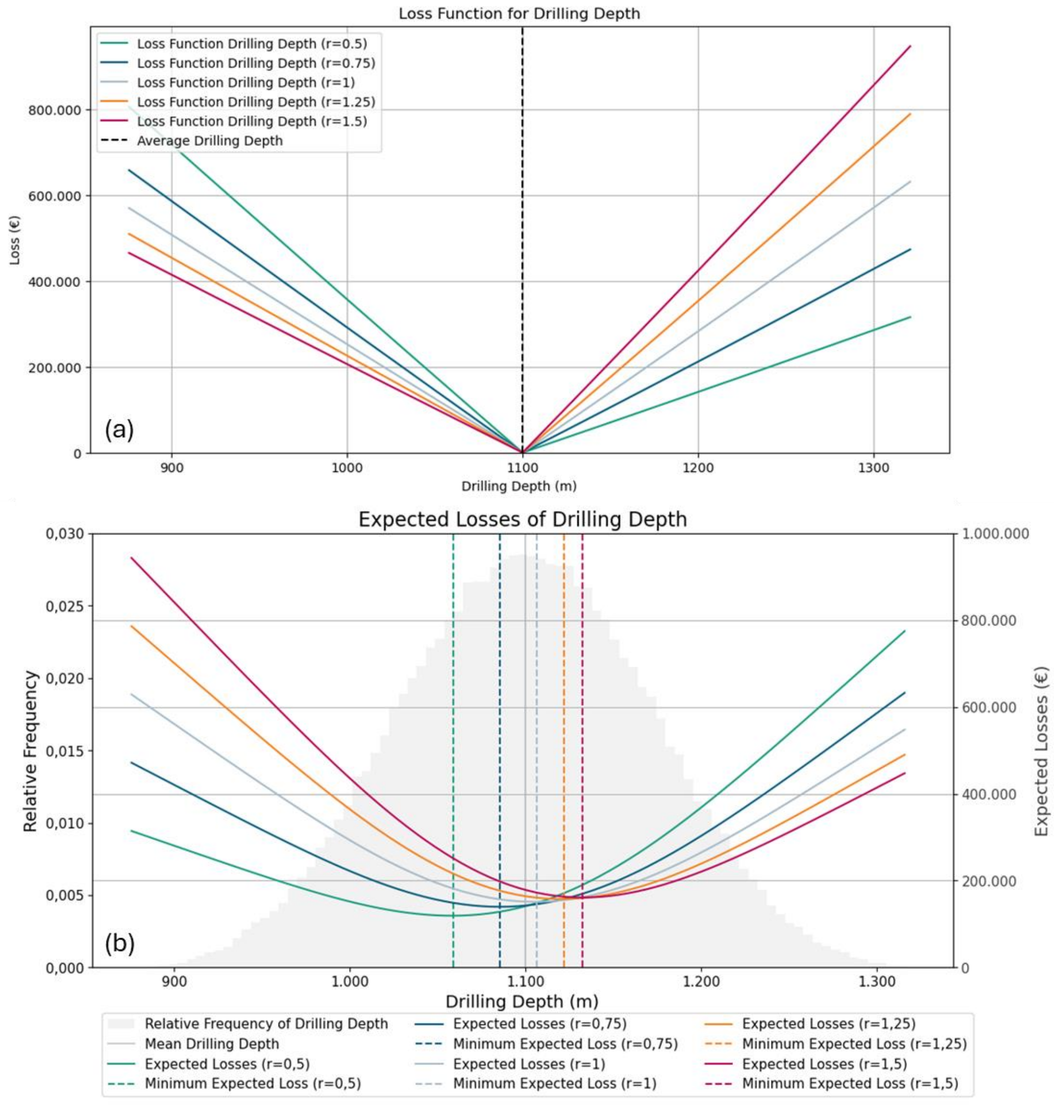

Figure 4: (a) Loss functions for drilling depth with different risk-affinities (r-values). (b) Estimated losses for drilling depth prior to acquisition of new data (here seismic data). (c) Estimated losses for the posterior drilling depth.

Table 1: Minimal expected losses for prior and posterior distributions of reservoir depth.

Risk factor	Minimal Expected loss [€]	Drilling depth [m]
0.5	119,230	1,058
0.75	139,765	1,085
1	151,284	1,106
1.25	157,732	1,122
1.5	161,158	1,132

Figure 3 (b) shows the expected losses for drilling depth till the shallowest stack of Dinantian carbonates. A risk-averse decision-making approach yields the smallest expected losses, but interestingly also the shallowest boreholes, shallower than the mean of the underlying uncertainty distribution. Analogue, the risk-affine decision maker has the highest expected loss, but also deeper estimated drilling depths. Overall, the expected losses range from around 120 k€ to around 160 k€ for different risk affinities, representing a range of expected drilling depths from 1,058 m till 1,132 m, which can be argued is a depth range allocated for in well-planning. However, it is worth to note, that the minimal expected losses due to uncertain depths of the Dinantian carbonates at the chosen drilling location already around 150 k€ (risk-factor = 1), i.e. around 7.5 % of total drilling costs for a 1.1 km deep drilling, taking the economic model of Thermogis (Vrijlandt, 2019). A next step in this approach would be to consider additional exploration activities, such as 2D seismics, and how these would affect the expected losses of drilling depth (see Pöschko et al., 2024). Applying this methodology to other uncertain parameters, such as expected flow rate of a geothermal doublet, could have an even greater effect.

3. CONCLUSIONS

This paper presents a model-based approach for analysis of geothermal exploration using methodologies rooted in information and decision theory, Efficacy of Information (EOI) and loss functions. The findings highlight the critical role of EOI in determining the optimal locations for exploration wells to reduce uncertainty, as well as the financial implications of misestimating drilling depths through the application of loss functions.

Three take away messages from this work are:

1. *Value of EOI*: EOI can be used as a tool to reduce uncertainty regarding the presence and depth of geothermal reservoirs by identifying exploration sites with the highest EOI. These can support the decision-making process in ranking drilling sites in a portfolio, ultimately leading to more efficient allocation of resources.

2. *Value of Loss functions*: Application of loss functions revealed that in presence of uncertainty, there will always be a loss, as expected and true value of a parameter will likely never match. Both, under- and overestimating the value, here drilling depths, can lead to distinct financial consequences. While the application to this example is likely within a risk-margin of planning of a geothermal well, other parameters, like predicted flow rate of a doublet, might have more severe financial implications.

4. *Future Research Directions*: The two methodologies applied in this study can be further expanded to incorporate additional exploration techniques, such as 2D seismic surveys. Extending EOI from two to three dimensions is the next step, so is investigating other uncertain parameters like expected flow rates using loss functions. Loss functions can be used in a Bayesian framework to estimate the Value of Information of further exploration activities.

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