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Uncertainty and Sensitivity Analysis for Geothermal Reservoir Performance and Techno-Economic Assessments: A Software Package for GEOPHIRES

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ABSTRACT

Stochastic simulation of geothermal reservoir models and economic assessments allows for probabilistic interpretations of reservoir favorability that may be used to inform geothermal project decisions. In 2018, the GEOPHIRES software was published as an open-source Python library for geothermal reservoir modeling and techno-economic calculations. This paper introduces an uncertainty and sensitivity analysis package for GEOPHIRES. Uncertainty in GEOPHIRES inputs may be specified for geological, thermal, utilization, and/or economic parameters. A Monte Carlo analysis is used to propagate those uncertainties through a specified geothermal reservoir model and economic calculations. Graphics of the reservoir performance over time are provided for the Monte Carlo replicates. Estimated reservoir performance and economic values are provided as summary statistics. Translation of the output variable uncertainties into decision-relevant information is provided by the estimated probability of achieving a specified temperature or heat production over time.

We demonstrate the use of this uncertainty analysis package with a case study that evaluates the feasibility of geothermal deep direct-use technology to meet the heating demands of the Cornell University main campus in New York State. A hypothetical target reservoir is known as the Trenton-Black River play, at approximately 2.3 km depth below Cornell. We evaluate several utilization scenarios consisting of different reinjection temperatures and flow rates. We use simple analytical reservoir models available in GEOPHIRES to illustrate the functionality of the package, although use of the package is not limited to the built-in reservoir models.

1. INTRODUCTION

Feasibility assessments for geothermal projects rely on forecasts of reservoir heat production over time, estimates of the heat utilization system performance, and calculations of economic costs. Geothermal techno-economic models are commonly employed for such assessments (e.g. Daniilidis et al., 2017; Olasolo et al., 2016; Sener and van Dorp, 2005). In the early phases of geothermal projects, and especially for new “greenfield” targets (e.g. Hadi et al., 2010), site-specific subsurface data are often limited. This results in potentially large uncertainties for various reservoir model parameters and economic costs (e.g. well drilling costs in Lukawski et al. [2016]). Translating uncertainty in techno-economic model input parameters into the uncertainty in decision-relevant information is critically important to evaluate the feasibility of a geothermal project, given the available data (e.g. Witter et al., 2019). Uncertainty propagation for techno-economic feasibility assessments can be employed during any phase of a geothermal project, with greenfield exploration expected to have the largest financial risk (uncertainty) – owing to the cost associated with drilling a productive first well or well pair (e.g. Lowry et al., 2017) – and decreasing risk over time as more is learned about the system (e.g. Robertson-Tait et al., 2015; World Bank, 2012, fig. 0.1).

In this paper, we introduce a stochastic evaluation of techno-economic models that allows for uncertainty analysis, sensitivity analysis, and probabilistic assessments of project favorability. We consider first the uncertainty in geothermal reservoir performance metrics that results from uncertainty in the input parameters. Then, we translate reservoir performance uncertainty into the probability of produced fluids to meet desired temperature and/or heat production thresholds over the plant lifetime. The probability of achieving certain reservoir performance favorability thresholds is reported, which is similar to methods developed for geothermal play-fairway analysis (e.g. Jordan et al., 2017). Finally, we propagate reservoir performance uncertainty into the uncertainty in economic costs. This feasibility assessment framework can provide quantitative support for a decision to invest in a well or invest in other means of acquiring site data (e.g. through value of information assessments in Trainor-Guitton et al. [2013] and Akar and Young [2015]).

We implement the uncertainty and sensitivity analysis methods in a new package for the GEOPHIRES software (Beckers and McCabe, 2019). GEOPHIRES is an open-source Python software that provides several options for techno-economic assessments, as described further in Section 2.

1.1 Paper Organization

This paper is organized as follows. Section 2 describes the framework of the geothermal reservoir and techno-economic modeling software, GEOPHIRES. Section 3 describes a new package for uncertainty and sensitivity analysis of GEOPHIRES models, and provides a discussion of options for analyses using this package. Section 4 demonstrates the functionality of the uncertainty and sensitivity analysis package using a case study that evaluates the feasibility of a geothermal deep direct-use system to meet the heating demands of the Cornell University main campus in Ithaca, NY, USA. For two geothermal reservoir models, we evaluate the uncertainty in heat production and economic costs. Sensitivity is evaluated for utilization scenarios that consist of different reinjection temperatures and flow rates. We conclude this paper with a discussion of the major capabilities of this software, and opportunities for probabilistic geothermal resource assessment, risk assessment, and economic project valuations.

2. GEOPHIRES TECHNO-ECONOMIC SIMULATION TOOL

GEOPHIRES (GEOthermal energy for Production of Heat and electricity ["IR"] Economically Simulated) is a computer simulation tool for performing a techno-economic analysis of a geothermal system (Beckers and McCabe, 2019). GEOPHIRES combines reservoir, wellbore, and surface plant technical models with cost and economic models to assess technical performance and cost-competitiveness of a geothermal system (Figure 1). Simulated output results include reservoir production temperature and heat extraction over time, generated electricity and/or heat, overall investment costs, levelized cost of energy, etc. The possible end-uses of the geothermal heat are electricity production, direct utilization of the heat, and combined heat and power. GEOPHIRES has built-in correlations for subcritical and supercritical organic Rankine cycle, and single- and double-flash power plants. Capital and operation and maintenance (O&M) costs are either estimated using built-in cost correlations (e.g. Lowry et al., 2017) or are provided by the user. The reservoir heat extraction is simulated by either using one of the built-in reservoir models (multiple parallel fractures [Gringarten et al., 1975]; one-dimensional linear heat sweep [Hunsbedt et al., 1984]; mass flow rate per unit area thermal drawdown [Armstead and Tester, 1987]; percentage thermal drawdown [Beckers, 2016]; plug flow), by specifying a generic user-provided temperature profile, or by coupling to an external reservoir simulator (e.g., TOUGH2 [Pruess et al., 2012]).

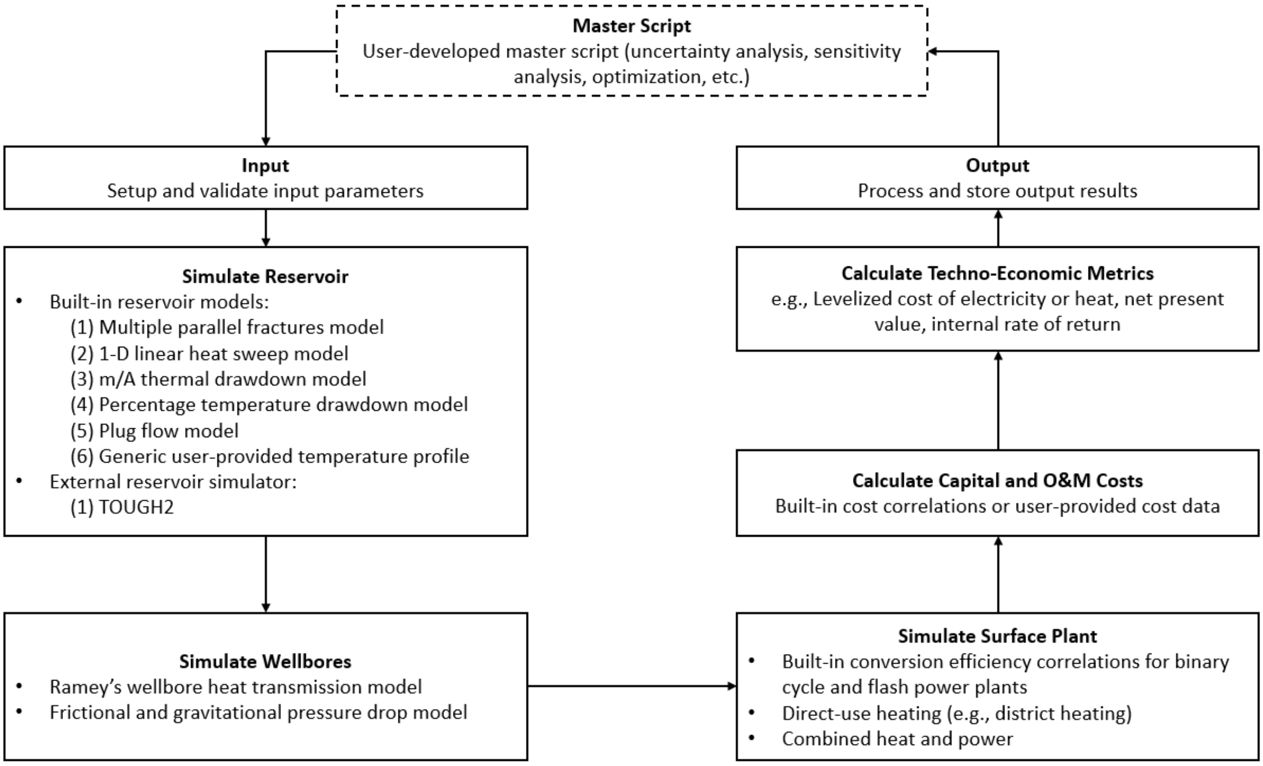

Figure 1: GEOPHIRES v2.0 techno-economic software architecture. A GEOPHIRES run involves setting up and validating the input parameters, simulating the reservoir, wellbores and surface plant, calculating the capital and O&M costs, estimating overall techno-economic metrics, and exporting the output results. A master script (developed by the user) can set up and run a set of simulations, e.g. optimization or Monte Carlo analysis.

2.1 GEOPHIRES Development History and Software Availability

GEOPHIRES builds on a long history of geothermal techno-economic modeling work. Initial work was performed as part of the Fenton Hill Hot Dry Rock (HDR) project at Los Alamos National Laboratory (Tester et al., 1979), which resulted in the HDR simulation tool (Armstead and Tester, 1987). This tool was upgraded to the MIT-HDR model in the late 1980's (Tester and Herzog, 1990) and eventually to the MIT-EGS tool in the 1990's (Kitsou et al., 2000) and 2000's (Tester et al., 2006). GEOPHIRES v1.0 built upon the MIT-EGS tool. Major upgrades included the option for simulating direct-use heat and combined heat and power, a new reservoir and economic model, and updated capital and O&M cost and power plant efficiency correlations (Beckers et al., 2013; 2014).

The latest version of GEOPHIRES (v2.0) was developed in the period 2017-2019 (Beckers and McCabe, 2018a; 2018b; 2019). This version was developed from scratch in Python (while the previous simulators were implemented in Fortran). Major upgrades included coupling GEOPHIRES to the numerical reservoir modeling software TOUGH2 (Pruess et al., 2012), updating all cost correlations, improving the wellbore heat transfer simulator and time step options, adding alternative wellfield configurations, and making the code open-source and available free of charge to all. The open-source Python code allows others to apply and modify GEOPHIRES for their projects, and improve upon the existing software.

As discussed in more detail in Section 3, for this project, the GEOPHIRES v2.0 Python code was modified to allow for accounting of subsurface parameter uncertainty, economic uncertainty, and heat utilization system uncertainty when performing geothermal reservoir simulations and techno-economic studies. A master script (Figure 1, Figure 2) was developed to perform a set of GEOPHIRES simulations (e.g. 10,000) for Monte Carlo analysis of the uncertain parameters. This allows for propagation of subsurface parameter uncertainties (e.g., geothermal gradient, rock thermal conductivity) economic uncertainties (e.g. cost of drilling), and utilization efficiency uncertainty to the uncertainty in overall geothermal system performance and economic costs.

3. UNCERTAINTY AND SENSITIVITY ANALYSIS PACKAGE FOR GEOPHIRES

A master script was developed to implement uncertainty analysis or sensitivity analysis for GEOPHIRES models using Monte Carlo simulations. The contents of the input file and the architecture of the master script are presented in Figure 2. The following subsections describe the details of the input file and the master script, and describe the types of output files and figures. Documentation for this input file, the master script, and other contents of the uncertainty analysis package are provided in the GEOPHIRES code repository on the "UncertaintyAnalysis" branch.

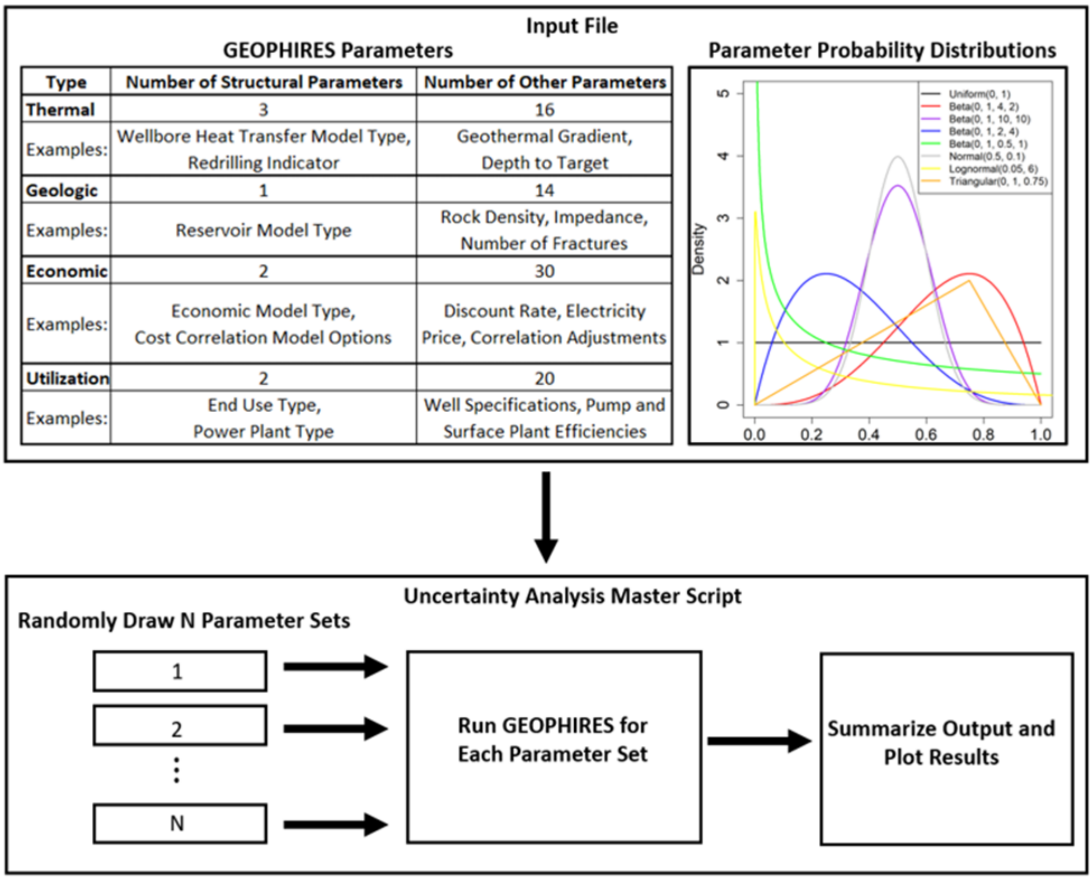

Figure 2: Input file contents and software architecture of the master script for uncertainty and sensitivity analysis of GEOPHIRES. The input file specifies probability distributions for each model parameter. Depicted in the table are the number of structural and "other" parameters for each parameter type in GEOPHIRES. Examples of each parameter type are also provided. The master script generates N random samples from the probability distribution of each parameter, runs GEOPHIRES N times, and summarizes the output. Probability distribution parameters: Uniform(lower bound [lb], upper bound[ub]), Beta(lb, ub, left shape, right shape), Triangular(lb, ub, mode), Normal(mean, standard deviation [std]), Lognormal(mean, std).

3.1 Input File Description

The input file consists of all of the possible GEOPHIRES model parameters and their corresponding probability distributions. Parameters are categorized for this paper into four types: thermal, geologic, economic, and utilization. For each type, there are structural parameters that determine which equations are used by GEOPHIRES, and there are "other" parameters that are required for specific equations. Thus, a subset of the total number of parameters are used in any GEOPHIRES simulation. Figure 2 lists examples of structural and other parameters for each parameter type, as well as the total number of parameters of each type. In the Section 4 case study, we list all of the relevant parameters for the two selected reservoir models in GEOPHIRES.

Uncertainty in structural parameters (i.e. model equations) represents epistemic uncertainty about the system being modeled. In other words, uncertainty in which equations are most appropriate to describe the system. Uncertainty in "other" parameters does not alter the techno-economic calculation equations, but does affect the values computed for output variables. For the purpose of uncertainty and sensitivity analysis, evaluating model output variables for different structural parameter choices would allow for the impact of particular equation assumptions to be discovered. For example, the impact of the selected reservoir model on the resulting thermal energy production and/or cost of the project may be of interest if the reservoir geometry is not well understood. In the Section 4 case study, we show results for two reservoir models to demonstrate the impact of epistemic uncertainty in reservoir geometry. We do not consider other epistemic uncertainties in this paper. To implement such an epistemic uncertainty analysis with this software package, one could use a multinomial distribution to select the equations used by a structural parameter for each Monte Carlo replicate.

For each parameter in the input file, a probability distribution and the corresponding distribution parameters (e.g. the mean and variance of the normal distribution) need to be specified. The distributions programed for use in this package include uniform, beta, triangular, normal, lognormal, and point distributions (i.e. Dirac delta functions); other distributions, such as those available in the scipy.stats Python library (Jones et al., 2001), may be added by users. Figure 2 exemplifies some shapes that these distributions could have. The beta and triangular distributions are flexible in the location of the most likely value (mode), which can be useful to describe parameters whose values tend to be skewed. Selecting a bounded probability distribution, like the beta, uniform, or triangular, can prevent the generation of physically unreasonable extreme values for parameters. The beta distribution is particularly useful for this purpose because it can be made to resemble several common unbounded distributions, like the normal (Figure 2). The upper tail of a beta distribution can be made to resemble a lognormal distribution (Figure 2), although the lognormal has an unbounded upper tail and zero density at the lower tail.

Point distributions are used for parameters that are fixed for all Monte Carlo replicates. Point distributions are useful if a particular parameter is well-known or has a relatively unimportant contribution to uncertainty in output variables. It is also useful to implement k-at-a-time or leave-k-out sensitivity analyses, where k is the number of parameters. When k is equal to one, first order and total order variance-based sensitivities could be computed, respectively, as described in Sobol' (2001). Alternatively, the SALib Python library could be used to implement these and other sensitivity analyses (Herman and Usher, 2017).

While any subset of parameters may be considered uncertain using this input file, selecting parameters by their type category can be informative to evaluate the impact that uncertainty in the parameters of a specific type have on the uncertainty of model outputs. For example, one might be interested in only the impact of geologic parameter uncertainties, holding parameters of all other types fixed at selected values. Saltelli and Tarantola (2002) describe the implementation of variance-based sensitivity analysis for such groups of model parameters. For geothermal projects, an analysis of parameter types within GEOPHIRES could provide an economic valuation for each parameter type. For example, one could determine the fraction of uncertainty in the cost of a project that results from uncertainty in thermal and geologic parameters, which in turn can inform decisions about data collection efforts.

Once the user has specified the probability distributions for each parameter, a Monte Carlo analysis is used to propagate the parameter uncertainties through the specified GEOPHIRES techno-economic models, as described in Section 3.2.

3.2 Master Script for Uncertainty and Sensitivity Analysis, and Summarizing Results

The master script (Figure 2) reads the input file and generates a specified large number, N, of random samples from the probability distribution of each of the parameters in the input file. GEOPHIRES is run once for each parameter sample for a total of N Monte Carlo replicates. The Monte Carlo replicates are run in parallel to reduce computation time. Computation time for the Monte Carlo analysis is generally limited by the time required to run the selected geothermal reservoir model, rather than the saving of figures and data files.

Once all of the Monte Carlo replicates have finished running, the GEOPHIRES output variable values are collected and summarized. For this package, an R script was developed to process the Monte Carlo output, and summarize and visualize results. R provides data processing and statistical analysis tools that were useful to analyze the GEOPHIRES data. The R script may be run directly from Python, as implemented in this package, or run as a standalone script.

For the thermal production and economic output variables, the mean, standard deviation, and selected quantile values are estimated from the Monte Carlo replicates. The probability of producing at least a certain temperature or thermal power value, or jointly producing at least both values is also computed. From those probability calculations, the year at which the probability is less than a specified value may be extracted. This time-to-probability computation may be useful for project planning purposes. These summary statistics are saved to Excel workbooks or comma separated files to allow results to be imported to further analyses not completed within GEOPHIRES.

Visualization of results is provided for all output variables. Histograms summarize the values of scalar quantities. Timeseries for variables that change over time are plotted with results from all replicates on a single plot. The computed timeseries of probability values are also plotted. Examples of these visualizations are presented in the figures in the Section 4 case study.

4. CASE STUDY OF DIRECT-USE HEATING FOR THE CORNELL UNIVERSITY CAMPUS

We apply the uncertainty and sensitivity analysis methods offered by this new package for GEOPHIRES to a feasibility assessment of using geothermal deep direct-use technology to meet the heating demands of the Cornell University main campus in Ithaca, NY, USA. The campus facilities are currently heated by a natural-gas-supplied steam district heating system. This system has an annual baseload heating demand of about 12 MW_{th}, with peak demands in the winter that exceed 80 MW_{th} (e.g. Gustafson et al., 2018, Fig. 3). In the summer months, heating is needed for domestic hot water and cooling system reheat. As part of an ongoing U.S. Department of Energy-funded feasibility study, deep (> 1 km) geothermal energy for the campus is being evaluated to initially meet a minimum of 20% of the total annual heating demand using an injection-extraction well pair in the target formation. This corresponds to about 5 MW_{th} continuous heat supply, considering system efficiency losses (Gustafson et al., 2019). Given the projected demands for the campus and planned renovations to campus buildings and the heating system to improve efficiency, it is expected that the thermal energy representing 20% of the annual demand will not change significantly over the useful lifetime of geothermal reservoirs (Gustafson et al., 2019). Further details about this Cornell feasibility study may be found in Tester et al. (2020).

We define feasibility in this paper as meeting two requirements over the operational lifetime of the geothermal direct-use system: 1) producing fluid at a temperature of at least 60 °C, and 2) producing thermal energy of at least 5 MW_{th}. Produced fluids that meet these requirements would jointly achieve the minimum building supply temperature for the Cornell campus, and meet the initial goal of 20% of the annual heating demand. Production of higher temperature fluid could be utilized in a thermal cascade (e.g. Gudmundsson et al., 1985) from higher and standard temperature campus facilities (80 °C and 70 °C minimum supply, respectively) to lower temperature facility needs, including animal housing, pasteurization, aquaculture, biomass drying, greenhouse warming, and snow melting (Gustafson et al., 2019). Heat extraction greater than 20% of the annual demand could be utilized to store thermal energy in hot water storage tanks and to meet additional space heating demands. Thus, we assume that all thermal energy produced by a geothermal reservoir will be fully utilized by the campus, less any efficiency losses.

Subsections 4.1 – 4.5 provide support for the techno-economic modeling choices and assumptions made for this paper. Table 2, presented after these subsections, summarizes the values and probability distributions selected for the model parameters. Justifications for the selected probability distributions are provided in Smith (2019). Generally, parameters with site data were assigned probability distributions similar to those observed. Parameters lacking site or regional data were assigned bounded triangular distributions based on the range and most common of the literature-gathered values. 1000 Monte Carlo replicates of these parameters were used to evaluate uncertainty in output variables.

4.1 Geothermal Resources below Cornell

The Cornell campus is located in the Appalachian Basin, which is classified as a low-temperature geothermal setting (e.g. Blackwell et al., 2011). Several geothermal resource assessments of the Appalachian Basin have estimated a region of elevated heat flow near Cornell (Smith, 2016; Stutz et al., 2015; Frone and Blackwell, 2010). The Cornell campus does not currently have a deep well, so the temperatures at target depths for geothermal reservoirs were gathered from estimates made in Smith (2019). Smith (2019) estimated temperature-depth profiles across the Appalachian Basin using a Monte Carlo analysis of uncertainty in a spatially correlated surface heat flow map (Smith, 2016; Jordan et al., 2017) and uncertainty in geologic properties in a one-dimensional vertical heat conduction model (Horowitz, Smith and Whealton, 2015).

The Smith (2019) temperature-depth profiles estimated for the Cornell campus are presented in Figure 3 for a 1 km^2 area that contains one of the proposed geothermal sites under consideration. Violin plots display the temperature uncertainty at each 0.5 km depth increment. The target reservoir for this paper is located at about 2.3 km depth within the Trenton-Black River (TBR) carbonate group, which regionally contains Darcy-scale permeability in a hydrothermally altered dolomite (Camp and Jordan, 2017). The Cornell Earth Source Heat team is also investigating other rock formations for geothermal fluid production, including the crystalline basement rock beginning at about 2.8 km depth, as discussed in Tester et al. (2020). Based on Figure 3, the Cornell campus target minimum building supply temperature of 60 °C could be achieved with near certainty within TBR rocks; temperatures suitable for higher temperature facilities may also be met.

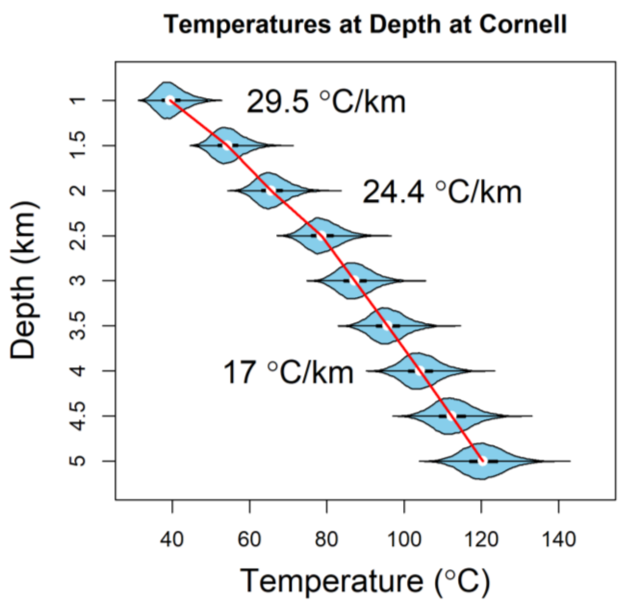

Figure 3: Predicted temperature-depth profile below Cornell University in Ithaca, NY, from Smith (2019). The uncertainty distribution of predicted temperatures for each 0.5 km depth interval is shown as a blue violin plot. White circles are placed at the median predicted temperature at each depth, and a narrow black box in the center spans the 25th to the 75th percentile estimates. Red line segments connect the predicted median temperature values for each depth. The thermal gradient corresponding to those lines is printed adjacent to the lines.

4.2 Geothermal Reservoir Target Formation

In south-central New York State near Cornell University, the contact of the Trenton and Black River formations contains dolomite where sub-vertical wrench faults extend upwards from basement rocks through the Black River limestones, and terminate at the upper contact of the Trenton, or within the immediately overlying Utica Shale (Smith, 2006; Camp and Jordan, 2017). The existence of Black River dolomite below Cornell depends on the presence of wrench faults, which have no surface expression.

Based on regional gas production fields (Camp and Jordan, 2017), if high permeability Black River dolomite exists below Cornell, the permeable thickness is expected to be about 30 m, and the spatial coverage area containing permeable zones is expected to have an elliptical shape with a minor axis about 1 - 3 km long. It is not known if the entire rock volume is likely to be permeable, or if permeability would be concentrated in zones, e.g., near the wrench faults (Camp and Jordan, 2017). Our analysis considers two conceptual representations of the geothermal reservoir that reflect these possible flow geometries, as described in Section 4.3.

Regional studies and oil and gas well data inform the characterization of uncertainty in values selected for key geologic properties of the TBR rocks, as described in detail within Smith (2019). Geologic property values that were not estimated from well log data were gathered from regional studies, when available, or studies of rock of comparable lithology at the thermodynamic conditions expected for the formation. Sources are provided in Table 1.

4.3 GEOPHIRES Reservoir and Wellbore Model Selection

We use two analytical reservoir models available in GEOPHIRES to model the end-member cases of conceptual reservoir flow geometries of the TBR play; the true reservoir flow geometry for this formation is likely in between these end member cases. The porous media plug flow model assumes that the entire reservoir is permeable, and provides an upper bound on the reservoir production lifetime. The parallel vertical fractures model approximates a fracture-dominated enhanced geothermal system (EGS) in which matrix permeability is negligible compared to flow through fractures. If high permeability zones do not exist in TBR rock below Cornell, an EGS could be attempted in TBR rocks using reservoir stimulation techniques (e.g. Breede et al., 2013). Fracture spacings of 20 m are assumed in models to limit thermal interaction between the fractures over the simulated lifetime of the geothermal system. Each of the porous media and fracture-flow models assumes that only the reservoir rocks will be amenable to fluid flow within the simulated rock volume. Equations describing these reservoir models may be found within the texts referenced in Section 2. A conceptual diagram of thermal drawdown for each model is provided in Figure 4.

For the multiple parallel fractures model, modifications were made to the GEOPHIRES software to add additional functionalities. These included (1) considering the geothermal gradient within the reservoir rock, and (2) allowing for vertical flow from the injection well (deeper) to the extraction well (shallower), as in Gringarten et al. (1975), instead of lateral flow through wells at the same depth.

For both models, the wellbore heat transmission model of Ramey (1961) is used for the extraction well to account for heat losses in shallower formations than the production depth. Such losses for this region are on the order of a few degrees Celsius, and are not negligible when evaluating project feasibility.

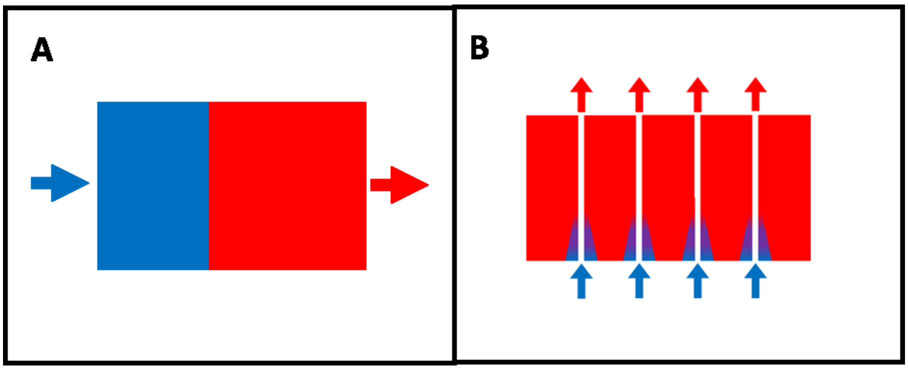

Figure 4: Conceptual diagrams for reservoir models after a lengthy time has elapsed. Each large rectangle represents an earth cross-section, with vertical and one horizontal dimension. Warmer temperatures are shown as red and cooler temperatures are shown as blue. Arrows represent well locations for injection (blue) and extraction (red). The injection well water is cooler than the reservoir rock. Initially the whole block would have been red. A) Porous media plug flow model. B) Parallel fractures model.

4.4 Utilization Scenarios

The sensitivity of reservoir heat production results to fluid flow rate and injection fluid temperature was evaluated for several well production scenarios. A summary of the production scenarios is provided in Table 1. Flow rates of 30 kg/s, 50 kg/s, and 70 kg/s were selected based on common values for operating geothermal systems (Snyder et al., 2017). The wellbore pipe size for 30 kg/s and 50 kg/s scenarios used a "small" inner diameter of 6.2" and the 70 kg/s scenario used a "large" inner diameter of 8.5" (Lowry et al., 2017). The temperatures of injected fluid were selected based on proposed surface utilization requirements for the Cornell campus. According to S. Beyers (personal communication, 2018), a reinjection temperature of 50 °C is the current district heating system return temperature for campus facilities, and this temperature would be appropriate if heat pumps were not used to extract additional energy. If heat pumps are used, 30 °C represents an optimal geothermal district heating system coefficient of performance (COP) of about 10. A temperature of 20 °C represents a lower limit of injection temperatures for which a heat-pump-assisted geothermal system COP would be more efficient than using the current natural gas-based system (COP of 3.5 - 4).

Table 1: Summary of production scenarios for geothermal reservoir simulations.

Well Flow Rate (kg/s)	Injection Fluid Temperature (°C)	Well Inner Diameter (in)
30	20	6.2
30	30	6.2
30	50	6.2
50	20	6.2
50	30	6.2
50	50	6.2
70	20	8.5
70	30	8.5
70	50	8.5

The distance between the injection well and the extraction well is limited by the area available on the Cornell site to space the wells and to directionally drill from the site. We evaluate 1 km well separation at depth for vertical wells in the TBR reservoir. For the parallel fractures model, 1 km horizontal wells are used, and the injection well is located below the extraction well. The vertical well separation distance is the 30 m thickness of the reservoir.

The capacity factor considers the fraction of the year that energy is extracted by the geothermal system. We assume capacity factors of 0.970 to 0.994, corresponding to a system being down for maintenance two to ten days on average per year.

4.5 Economic Assumptions

Capital and operation and maintenance (O&M) costs are computed assuming several correlations provided in GEOPHIRES. In this paper, capital expenses considered only well drilling because Cornell has existing financial resources to update the surface infrastructure for hot water district heating (S. Beyers, personal communication, 2018). O&M costs considered the price to make up water that is lost in the system, the price of electricity for pumping water through the well network, the cost of maintaining wells, and the cost of operating the district heating plant. These correlations are adjusted by ±20% to reflect uncertainty in their estimation. The electricity price is determined by the range of typical rates for the Cornell campus (S. Beyers, personal communication, 2018).

The capital and O&M costs estimated in this paper may be used in probabilistic calculations of the levelized cost of heat (LCOH). The resulting LCOH distribution can be compared to market prices of alternative heating fuels to evaluate competitiveness of the geothermal system. A discussion of the site-specific levelized cost of heat for the Cornell feasibility study is presented in Tester et al. (2020).

Table 2: Summary of parameters used in GEOPHIRES models. Probability distributions are listed for those parameters that were selected randomly within Monte Carlo simulations. Probability distributions: Triangular(lower bound [lb], mode, upper bound [ub]), Normal(mean, standard deviation [std]), Lognormal(real space mean and std). Beta(left shape parameter, right shape parameter, lb, ub).

GEOPHIRES Parameter Type	Parameter	Model: Trenton-Black River Plug Flow	Model: Trenton-Black River Parallel Fractures	Notes and Sources
Thermal	Surface Temperature (°C)	Triangular: 8, 10, 12	Triangular: 8, 10, 12	Gass (1982), SMU Geothermal Lab (2016); matches assumptions in Smith (2019)
	Geothermal Gradient (°C/km)	0 – 1.5 km: Triangular: 26.5, 29.5, 33.7 1.5 – 2.8 km: Triangular: 23.7, 24.4, 25 2.8 – 4 km: Triangular: 16.5, 17, 17.5	0 – 1.5 km: Triangular: 26.5, 29.5, 33.7 1.5 – 2.8 km: Triangular: 23.7, 24.4, 25 2.8 – 4 km: Triangular: 16.5, 17, 17.5	Figure 3 in this paper, from Smith (2019)
Geologic	Reservoir Depth (km)	2.27 - 2.30	2.27 - 2.30	Local well formation top interpolation (T.E. Jordan, personal communication, 2018; J.A. Al Aswad, personal communication, 2018)
	Well Orientation in Reservoir	Vertical	Horizontal	
	Reservoir or Fracture Height (m)	30	30	Camp and Jordan (2017)
	Reservoir or Fracture Width (m)	1000	1000	Camp and Jordan (2017)
	Reservoir or Well Lateral Length (m)	1000	1000	Camp and Jordan (2017)
	Fracture Separation (m)	NA	20	
	Fracture Width (mm)	NA	0.5	Camp and Jordan (2017)
	Reservoir Impedance (GPa-s/m^3)	Triangular: 0.05, 0.15, 0.5	Triangular: 0.05, 0.15, 0.5	Camp et al. (2018) regional reservoir productivity
	Rock Density (kg/m^3)	Normal: 2800, 40	Normal: 2800, 40	Local well logs
	Rock Porosity (-)	Lognormal: 0.08, 0.046	NA	Local well logs
	Rock Heat Capacity (J/kg-K)	Triangular: 900, 930, 940	Triangular: 900, 930, 940	Roberson and Hemingway (1995)
	Rock Thermal Conductivity (W/m-K)	Triangular: 1.92, 2.91, 3.9	Triangular: 1.92, 2.91, 3.9	Cornell University (2016), matches assumptions in Smith (2019)
Utilization	Utilization System Capacity Factor (-)	Beta: 4, 2, 0.97, 0.994	Beta: 4, 2, 0.97, 0.994	Allows for two to ten days on average per year for maintenance.
	Pump Efficiency (%)	Triangular: 68, 73, 78	Triangular: 68, 73, 78	S. Beyers (personal communication, 2018)
	Water Loss Rate (%)	Triangular: 1, 2, 5	Triangular: 1, 2, 5	
Economic	Cost Correlation Multipliers: Well, Makeup Water, Surface Plant, Wellfield Operation	Beta: 2, 2, 0.8, 1.2	Beta: 2, 2, 0.8, 1.2	
	Electricity Price for Pumps (USD/kWh)	Triangular: 0.03, 0.0315, 0.033	Triangular: 0.03, 0.0315, 0.033	S. Beyers (personal communication, 2018)

4.6 Case Study Results

The temperatures of produced fluids estimated from analytical modeling of the TBR reservoir are shown in Figure 5 for an injection temperature of 30 °C and a pumping rate of 50 kg/s. Figure 5 illustrates temperature-time curves that are characteristic of each reservoir model. For the parallel fractures model with vertical flow, rock temperature at the top of the fracture is initially cooler than the rock temperature at the bottom of the fracture. Over time, rock at the top of the fracture is warmed to at most the rock temperature at the bottom of the fracture. For the porous media plug flow model, a sudden drop in the produced temperature occurs once thermal breakthrough of the cold thermal front reaches the extraction well. For both geothermal reservoir models, extraction well borehole heat transfer cools the water along the length of the extraction well; the effect of wellbore cooling decreases over time as the extraction borehole warms.

Figure 5 also shows the range of production temperatures that result from uncertainty in the initial temperature conditions (Figure 3). For the plug flow model, uncertainty in the produced temperature decreases after thermal breakthrough as a result of the majority of the thermal energy having been extracted from the reservoir. For both models, uncertainty in the time to thermal breakthrough is right skewed with a range of about 2 years. Based on the Monte Carlo replicates, the joint probability of meeting the 60 °C and 5 MW_{th} minimum requirements for the Cornell system falls below 95% after 8 - 12 years of operation for this production scenario. It is not possible to achieve a 95% probability of meeting 70 °C and 5 MW_{th} requirements for standard temperature Cornell facilities with this production scenario.

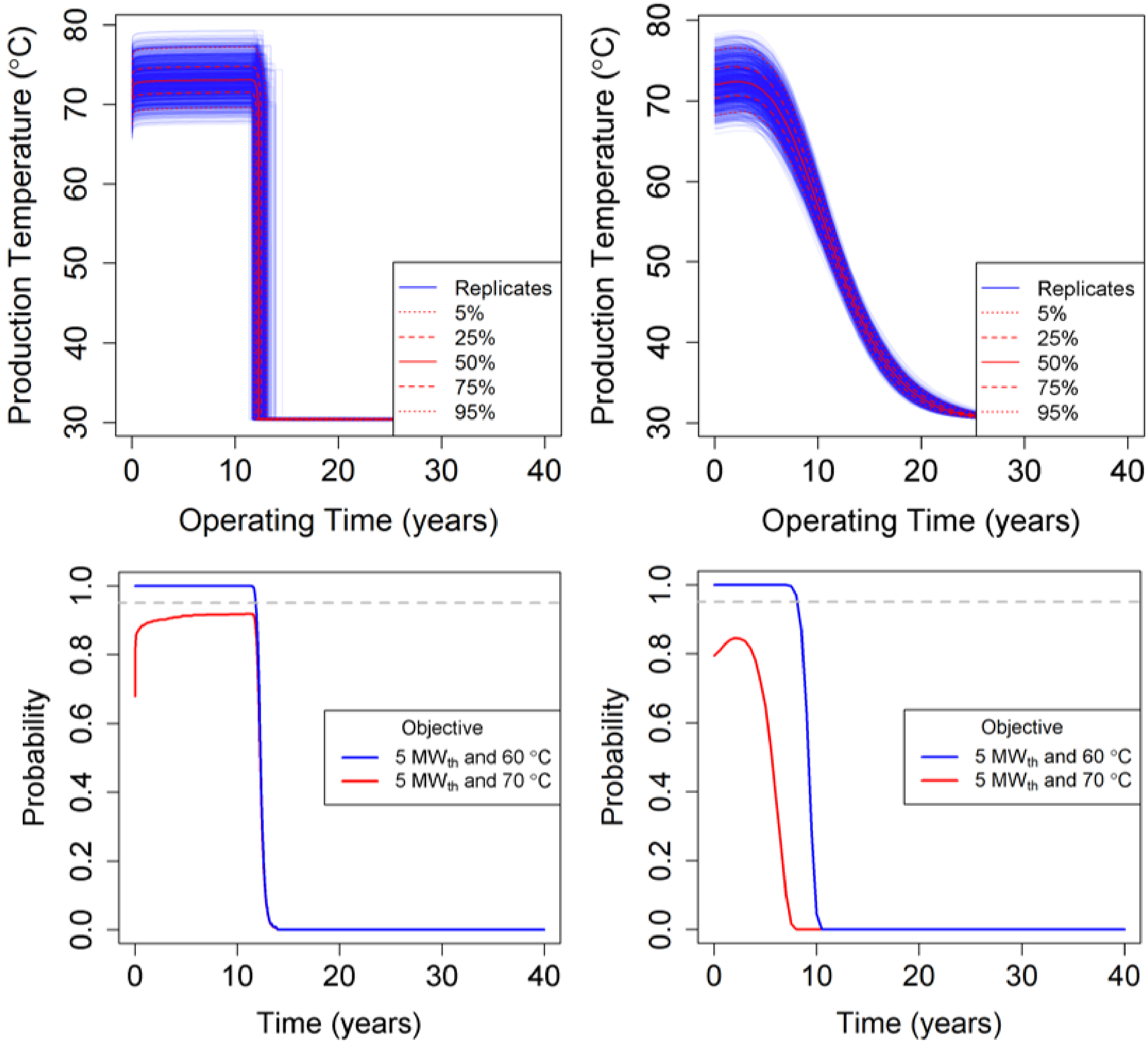

Figure 5: Top Row: Production temperature over time for the TBR reservoir using the plug flow model (left) and the parallel fractures model (right). The injection temperature is 30 °C and the flow rate is 50 kg/s. Each blue line provides the results of a single Monte Carlo replicate. Selected quantiles over time are provided in red. Bottom row: The probability of meeting the listed objectives over time. The horizontal dashed gray line is located at 95% probability.

Figure 6 summarizes the joint probability of producing fluids that meet both the 60 °C and the 5 MW_{th} heating objectives for each of the production scenarios and reservoir models. We consider the necessary condition for successful operation of the geothermal system to be a high joint-probability of meeting the objectives, and therefore identify an estimate of the useful life span of the geothermal system to be the time at which the joint probability of meeting the objectives is less than 95%. If these analytical models bound the possible flow geometries of a reservoir, the range in useful life estimates for a production scenario may be interpreted as an estimate of the time that thermal breakthrough is likely to begin. Using these criteria, a flow rate of 30 kg/s with an injection temperature of 20 °C dominates the other scenarios in expected useful life.

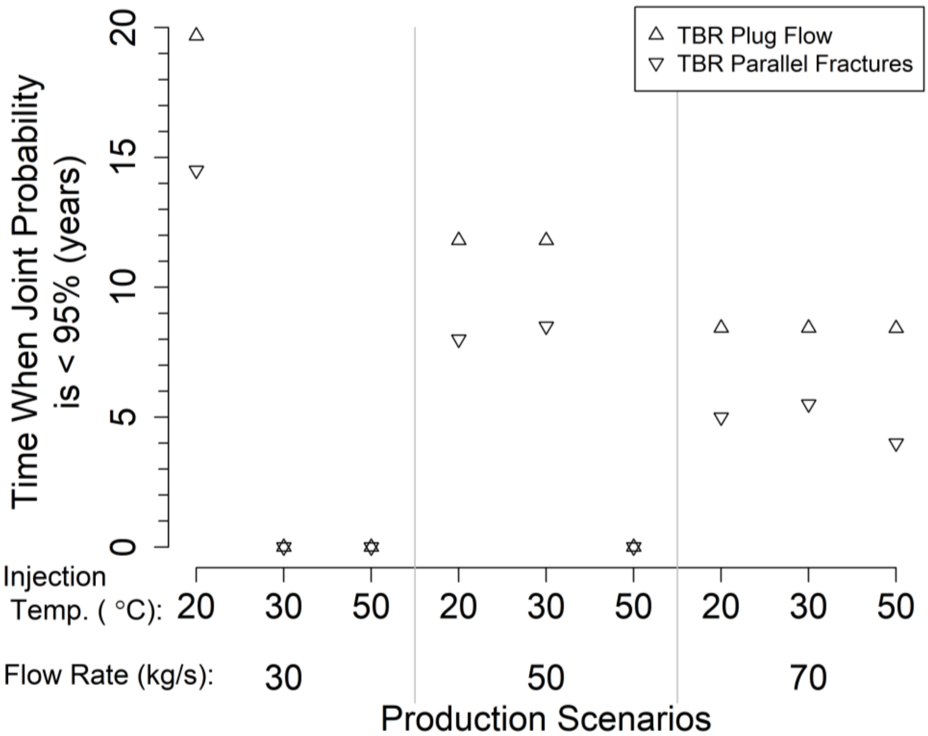

Figure 6: The time after geothermal production began at which the joint probability of a TBR production scenario meeting a temperature of 60 °C and heat production of 5 MW_{th} declines to less than 95%. Results are shown for the plug flow porous media model (upward pointing triangles) and parallel fractures model (downward pointing triangles). Where both models estimate similar performance, the overlap of the two symbols makes a star.

Figure 7 provides the capital and O&M costs associated with the more favorable 30 kg/s and 20 °C production scenario. The O&M costs for both reservoir models are similar. The capital cost of the parallel fractures model is about $0.5 million greater than the plug flow model as a result of horizontal well drilling expenses. Using these Monte Carlo results, the probability of certain expenses can be extracted.

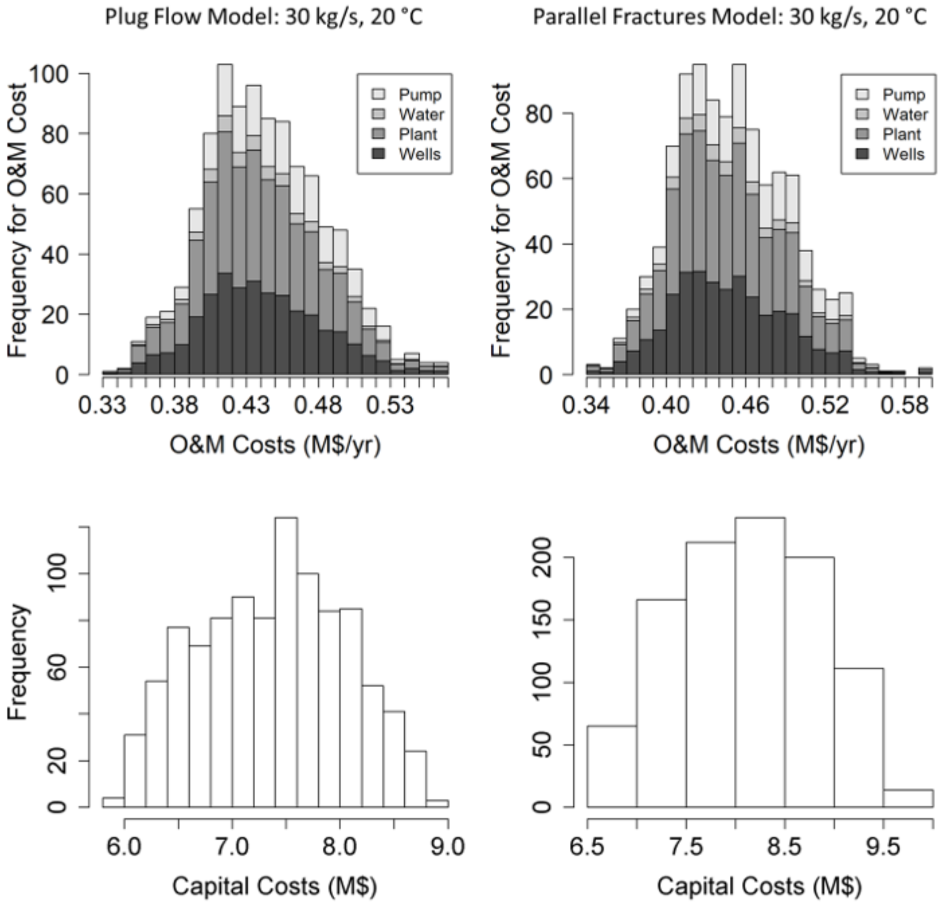

Figure 7: Histograms of the capital costs and O&M costs estimated from Monte Carlo simulations for the 30 kg/s flow rate and 20 °C injection temperature scenario. Left: plug flow model, Right: parallel fractures model.

5. CONCLUSIONS

The ultimate value of an uncertainty analysis is the impact on the risk and economic valuation of a project. For techno-economic models, uncertainty in the output from the technical models results in uncertainty in the input to the economic models. We presented an uncertainty and sensitivity analysis package for geothermal reservoir performance and techno-economic assessments that propagates uncertainty and allows for probabilistic assessment of project favorability. We demonstrate computation of favorability using the probability of producing at least a certain temperature or thermal power value, or jointly producing at least both values. From those probability calculations, the year at which the probability is less than a specified value is extracted. Results from such analyses may be used to inform techno-economic evaluations, and determine which of the uncertain parameters or groups of parameters contribute most to overall project techno-economic uncertainty. These evaluations can inform which parameters to focus on for future data collection to reduce uncertainty before the expensive investment of drilling a first well at a site.

The GEOPHIRES software provides tools for analytical modeling of geothermal system performance and economic calculations. The open-source Python code allows others to apply and modify GEOPHIRES for their project, and improve upon the existing software. The uncertainty and sensitivity analysis software package for GEOPHIRES presented in this paper allows for aleatoric uncertainty analysis relating to model parameter uncertainty, as well as epistemic uncertainty analysis relating to the structural model assumptions (e.g. reservoir model, wellbore model, economic model).

We demonstrated the use of the uncertainty analysis package using a case study to evaluate the feasibility of geothermal deep direct-use heating of the Cornell University main campus. We used two analytical geothermal reservoir models that are available in GEOPHIRES to show the impact of epistemic uncertainty in reservoir flow geometry. O other reservoir models, such as numerical simulators, could also be linked to this software. This allows for updating uncertainty in the geothermal performance and economics of a project to reflect the state of knowledge or belief about a system as more data are collected and as models are improved.

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7. CODE AND DATA AVAILABILITY, AND SOFTWARE CREDITS

The GEOPHIRES software is open-source and available in a GitHub repository (Beckers and McCabe, 2018b). The uncertainty and sensitivity analysis master script developed for this paper is available on the "UncertaintyAnalysis" branch in that repository. The input data files needed to reproduce the results presented in the paper are also located on the UncertaintyAnalysis branch.

Statistical analyses and plotting functions were developed using R version 3.5.0 (R Core Team, 2018) and the packages abind (Plate and Heiberger, 2016), dataframes2xls (van Steen, 2016), doParallel (Microsoft Corporation and S. Weston, 2017), Hmisc (Harrell Jr. et al., 2018), and readxl (Wickham and Bryan, 2018).

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