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Development of a Geothermal Module in reV:

Quantifying the Geothermal Potential while Accounting for the Geospatial Intersection of the Grid Infrastructure and Land Use Characteristics

Paul Pinchuk, Sophie-Min Thomson, Whitney Trainor-Guitton, Grant Buster, and Galen Maclaurin

National Renewable Energy Laboratory

Keywords

Geospatial, grid infrastructure, exclusions, geothermal resource data

ABSTRACT

The Renewable Energy Potential (reV) model is a geospatial platform for estimating technical potential and developing renewable energy supply curves, initially developed for wind and solar technologies. The model evaluates deployment constraints, considering land use, environmental, and cultural factors, and estimates the distance to existing grid features to connect future plants (Maclaurin et al., 2021). A pressing deficiency in the reV model, however, is representation of geothermal electricity generation technologies.

To address this gap, we developed a novel geothermal generation module for reV that allows for representation and analysis at the same level of detail as other renewable technologies. This paper describes our process for evaluating data sources for the modeling, and presents five preliminary reV geothermal results. More specifically, we present two sets of resource data that represent upper and lower bounds for geothermal potential. We then present several sensitivity runs using the upper bound resource data; the results are encouraging that levelized cost of electricity (LCOE) can be reduced by optimizing the location and estimated capacity of the spatially diverse geothermal resource while considering the distance to existing grid infrastructure.

Our preliminary supply curves and levelized cost of electricity (LCOE) results should be considered with care due to the highly uncertainty in geothermal resource potential data. We present median LCOE values for the conterminous U.S. for five scenarios: four hydrothermal (3.5km depth) and one EGS (4.5km depth). The capital and operating costs for each respective technology are modeled. We also compare results using two different resource data sources.

1. Introduction

Modeling the potential future deployment of renewable energy generation across the United States is a complex techno-economic equation that minimizes costs and maximizes power production, while abstracting considerations of siting constraints, environmental and ecological impacts, and social acceptance from local communities. This is a challenging optimization that has many potential solutions depending on the assumptions and scenarios in the model representation. In power system modeling at the National Renewable Energy Laboratory (NREL), these deployment considerations are represented between two models: The Renewable Energy Potential (reV) model and the Regional Energy Deployment System (ReEDS). The reV model is a geospatial platform for estimating technical potential and levelized cost of energy (LCOE) and for producing supply curves for renewable energy resources (initially wind and solar). The model evaluates land access constraints that represent siting considerations for plant development and estimate the distance to existing grid infrastructure. ReEDS is NREL's flagship capacity expansion model, which models the future evolution of the bulk power system. ReEDS is a forward-looking model that optimizes future build-out and retirements of generators given a set of technology cost assumptions and electricity demand projections. ReEDS takes the reV supply curves as inputs to represent the available capacity, and associated plant performance and interconnection costs, to optimize the least-cost power mix that meets the scenarios constraints and operating requirements of the bulk power system (Ho et al., 2021).

A pressing deficiency in the reV model is representation of geothermal electricity generation technologies to evaluate the potential at spatial parity with wind and solar. Because of this, the ReEDS model cannot represent geothermal technologies with an appropriate spatial fidelity compared to wind and solar.

Since the U.S. transmission system was initially built to connect load with central fossil fuel power plants, access to transmission for renewable resources, which are spatially dependent, is an ever-growing constraint. Geothermal resources are highly site dependent and, in some cases, developing new plants will require long and costly spur lines (or generation tie lines). Adequately capturing the potential investment costs is needed to evaluate geothermal generation potential against other technologies. The reV model simulates generation tie line routing and costs to connect hypothetical new plants to the existing transmission infrastructure (lines and substations). The reV model is the underlying geospatial engine that affords ReEDS the implicit high-fidelity representation of siting constraints and transmission access. This common framework will enable direct comparison and cost optimization for potential geothermal plants.

1.1 reV Background

The reV model couples directly with NREL's System Advisor Model (SAM) to batch simulations of power production and costs for photovoltaic (PV), concentrating solar power (CSP), and land-based and offshore wind energy technologies (Buster et al., 2023). The reV model is state-of-the-art in technical potential and supply curve modeling and is an integral component of NREL's capabilities to model the future evolution of the U.S. bulk power system, along with ReEDS and production cost and power flow models (Figure 1). Modules in the reV framework function at different spatial and temporal resolutions, allowing for assessment of resource potential, technical potential, and supply curves at varying levels of detail. The model was initially designed to focus on spatially continuous and temporally variable renewable energy, such as wind and solar. However, the strengths of the model, particularly transmission access and land use considerations, also apply to other renewable energy technologies and the spatial and temporal characteristics of a generator do not preclude the representation in reV.

NREL's power systems models (including reV and ReEDS) are used to inform the deployment pathways for renewable technologies to meet clean energy targets set at the municipal, state, and federal levels. Additionally, many private and public utilities, system operators, and energy consortiums rely on NREL's modeling capabilities to inform their strategic energy planning.

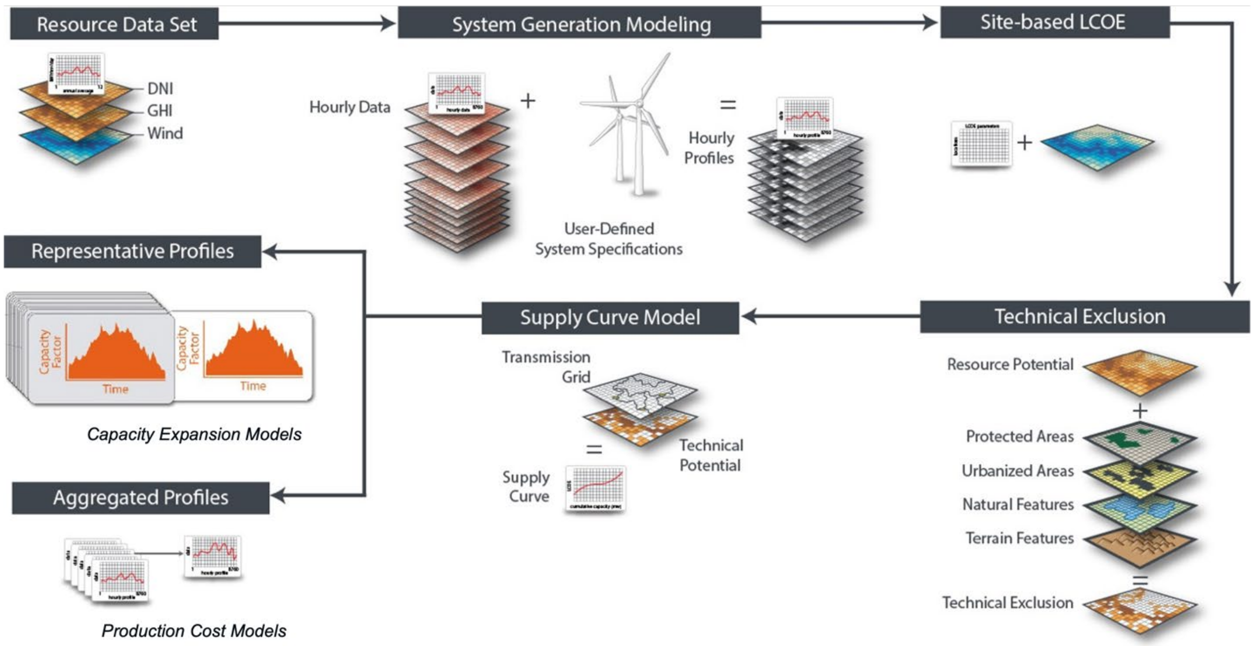

Figure 1: reV workstreams. The first workstream uses resource data to calculate generation and LCOE; the second applies technical exclusions according to different land type and ecological features.

The platform runs on NREL's high-performance computing system, providing scalable and efficient performance from a single location up to a continent, for a single year or decades of time-series resource data. The model is also configured to run on the cloud, specifically on Amazon Web Services. Coupled with NREL's SAM, reV supports the analysis of long-term variability of renewable generation (e.g., interannual variability and exceedance probabilities), which is important for wind and solar, but less so for geothermal.

1.2 New Capabilities

This project brings representation of geothermal electricity generation closer to parity with wind and solar technologies in reV, and thus in downstream bulk power system models. The principal focus on abstracting real-world siting constraints and transmission interconnection costs for utility-scale geothermal electricity plants is of high importance for developers, utilities, public land managers, and energy planners. The new geothermal module in reV relies on the U.S. Department of Energy's Geothermal Electricity Technology Evaluation Model (GETEM) implemented in SAM (Blair et al., 2018). Modeling approaches are implemented for hydrothermal reservoir systems and enhanced geothermal systems (EGS). We have developed the module to be flexible and extensible such that geothermal supply curves can rely on different geothermal resource datasets, support a wide range of deployment assumptions, and accommodate future improvements to data and modeling approaches.

The reV model is designed at its core to be flexible, extensible, and easy to use. The model was open-sourced in 2020 and has since seen broad adoption and use across the private and public sectors. External collaborators help establish new research directions and priorities for model development.

The U.S. energy sector currently lacks a national-scale technical potential and supply curve tool to evaluate the opportunities and barriers for utility-scale geothermal power production on a level playing field with wind and solar. Understanding the relative technical potential for geothermal will better inform policy and planning for a high penetration of renewable energy.

1.3 Geothermal Technical Potential

Initially, technical potential was only represented in reV for wind and solar, utilizing information about the available land and corresponding weather data (Maclaurin et al., 2021). The National Solar Radiation Database (NSRDB) (Sengupta et al., 2018) and the Wind Integration National Dataset (WIND) Toolkit (Draxl et al., 2015) provide high spatial and temporal resolution of the solar and wind potential. reV calls SAM—which provides detailed performance and financial analysis for renewable energy systems—by representing the supply and costs of different sources of energy. This modeling approach is fully compatible with evaluation of geothermal potential. On the back end, SAM uses the GETEM model, which requires temperature, depth, and resource potential in megawatts (MW) as inputs. The functionality of GETEM within SAM enables seamless integration with reV to represent geothermal technologies.

Technical potential is calculated as a function of the following: The available land area (in km^2) after applying spatial exclusions that represent siting constraints for plant deployment; the net capacity factor (after applying system losses) estimated by the generation module given the site-specific resource (Section 2.2); and a power density (PD) appropriate for the specific technology, which represents the maximum potential capacity for a given unit of area (in MW/km^2). The technical potential for a year (8,760 hours/year) is calculated as follows:

$$\textit{Annual technical potential}\ (MWh) = area * PD * CF * 8{,}760 \tag{1}$$

where PD is the power density (MW/km^2) and CF is the annual net capacity factor of the generator (as a percentage).

The power density estimation is difficult for geothermal resources as it ideally includes estimates of heat, permeability, and fluids (for conventional geothermal) at deep depths, and spatially exhaustive observations of these properties do not exist. Thus, many challenges exist in representing the geothermal technical potential with certainty. The following sections discuss these challenges, within the context of data limitations (Section 1.3.1) and potential solutions (Section 2.3).

1.3.1 Data Sources

We examined several datasets to evaluate the integration of geothermal resource representation into the reV software. We prioritized datasets that had comprehensive spatial coverage to fully exploit the capacity of reV to quantify supply curves.

Table 1: Potential data sources of geothermal resource estimates

Data Source	Spatial Extent	Count/Aerial Resolution	Depth Resolution	Units	Reference
USGS Favorability 2008	Western U.S.		None	Undefined	(Williams et al., 2008)
USGS Heat Flow	Great Basin Region	250m x 250m = 0.0625km^2	None	milliWatts/m^2	(DeAngelo et al., 2022)
SMU Temperatures	Conterminous U.S.	2.5km x 2.5km = 6.25 km^2	3.5km – 10km depth increments of 1km	Degree C	(Blackwell et al., 2011)

The temperature at depth datasets from Southern Methodist University (SMU) (Blackwell et al., 2011) were initially selected as the preferred dataset to represent conterminous U.S. geothermal resources, as they provided the most comprehensive representation of geothermal data, both spatially and in the depth dimension (see Figure 2). The USGS Favorability data (Williams, 2008), which had a qualitative nature, did not provide the quantitative temperature, depth, and resource potential inputs required by SAM/GETEM. The 2022 USGS heat flow dataset (Figure 3) is an update from the SMU heat flow, but only covers the larger Great Basin region and, like the SMU heat flow information, does not provide any data regarding the depth of the resource (DeAngelo et al., 2022). Depth is a critical quantitative input required by SAM/GETEM.

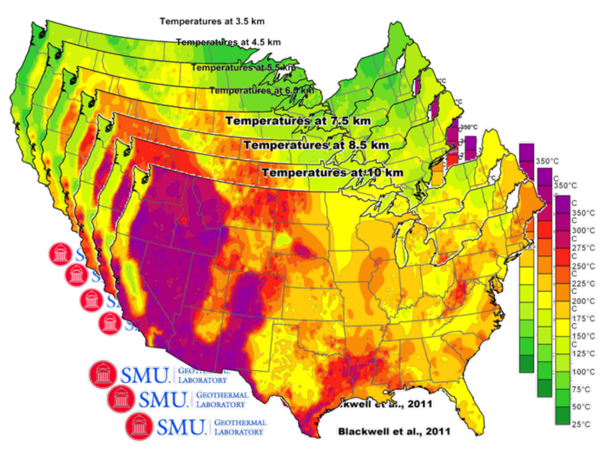

Image Source: Blackwell et al. 2011

Figure 2: SMU maps of temperatures at depth

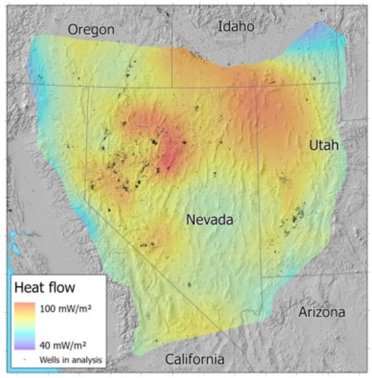

Figure 3: USGS heat flow map for the Great Basin region (DeAngelo et al., 2022)

An essential parameter necessary for conducting a SAM/GETEM simulation at each reV site is the nameplate capacity of the plant under consideration. To estimate this value from the SMU temperatures, we relied on an exponential relationship formulated by (Wilmarth et al., 2021)

$$\text{Resource potential } [MW] = 0.408{*}\exp^{(0.014\ \text{Temperature}[C])} \tag{2}$$

This empirical model relates the reservoir temperature to a power density value for 103 pre-existing geothermal plants globally (Figure 4). Hence, we computed a corresponding power density value for each temperature value in the resource dataset and transformed it into a plant capacity value based on the size of our SMU resource cells, which measure 6.25 km^2. For the Great Basin region, the average power density resulted in approximately 15 MW per 6.25 km^2 cell using the SMU temperatures in the exponential function.

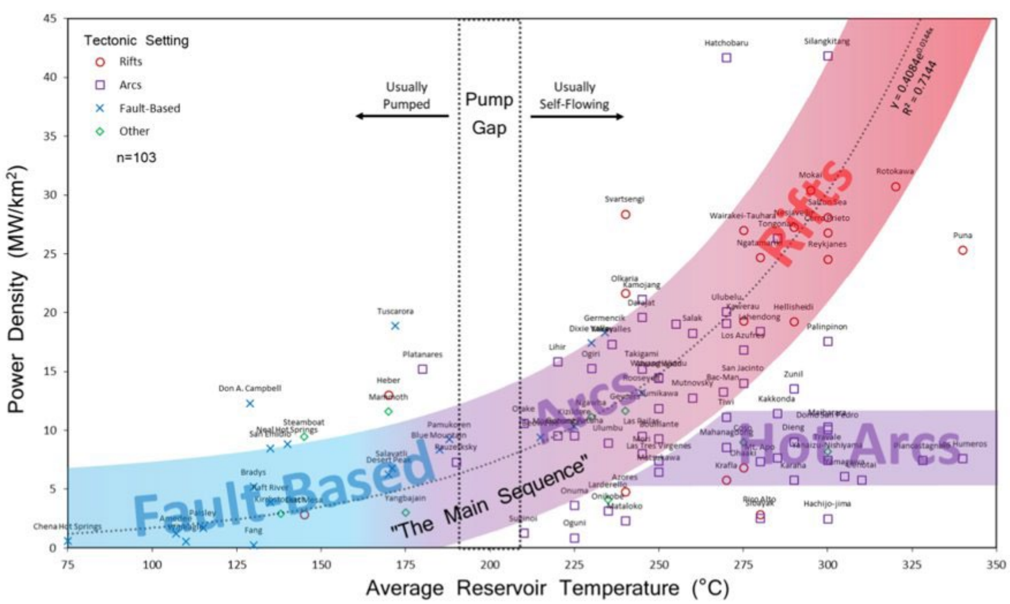

Figure 4: Exponential relationship used to convert SMU temperatures to megawatts, based on 103 geothermal fields (from Wilmarth et al., 2020)

For the USGS dataset, which was in milliwatts, the power density was obtained by multiplying the milliwatts by the area of each cell (0.0625 km^2). The average of this dataset is 78.64 mW/m^2

(0.07864 MW/km^2). An important note of this heat flow calculation is that interpolated heat flow results were created using a process that sought to remove hydrothermal convective influence from predictions of background conductive heat flow. As explained in the documentation of DeAngelo et al. (2022), this heat flow map was "constructed using a custom-developed iterative process using weighted regression, where convectively influenced outliers were de-emphasized by assigning lower weights to measurements with heat flow values further from the estimated local trend (e.g., local convective influence)." This indicates that the values will not contain higher outliers or anomalies, which are exactly what geothermal prospectors are looking for. Therefore, estimates from this map may represent a lower bound of geothermal potential.

The resource potential (nameplate capacity) serves as a fundamental parameter required by SAM/GETEM to compute the number of well replacements over the operational lifespan of a geothermal power plant. However, to ensure congruence with modeling approaches adopted for other renewable technologies such as solar and wind, which do not consider changes in the plant over time, we have decided to exclude the modeling of well replacements in reV. Instead, we have simplified the modeling process by setting the resource potential equal to the gross generation potential as determined by the nameplate capacity of the geothermal plant.

1.3.2 Data Format

The temperature at depth datasets from SMU were transformed into an equal-area raster format, with each cell measuring 2.5 km x 2.5 km (6.25 km^2). Each depth layer was stored separately within a single Hierarchical Data Format version 5 file (HDF5). Users can extract temperatures between the depth ranges specified by the original data, which are computed using linear interpolation. For each depth layer, a corresponding resource potential layer was computed. USGS data were provided in GIS format.

1.3.3 Data Filters

Some combinations of temperature and depth values sourced from SMU data fell outside the range of assumptions underlying the GETEM model. To alleviate the errors stemming from this input data discrepancy, we implemented supplementary filters on the data prior to feeding it into SAM/GETEM. Our approach restricts the execution to specific locations where resource temperatures fall within the range of 120–325°C and excludes depths greater than 7 km from the model.

1.4 Geothermal Spatial Exclusions

The users of reV can limit the development by land ownership, terrain, land use/cover, urban areas, and custom inputs. . The model allows for spatial exclusion with the input layers or summary of outputs by layer (i.e., using the layers for filtering rather than excluding areas). This enables users to run different scenarios and evaluate outputs by spatial layers (e.g., to quantify the technical potential on public lands). Geothermal shares some of the same sensitivities as solar and wind development (e.g., ecological habitats) but has additional leasing considerations that make public versus private lands an important consideration when estimating capacity expansion.

Table 2: Spatial exclusion layers considered

Layer	Square Kilometers	Type	Source	Percentage of CONUS
Federal Lands	1,106,975	Land Ownership	ESRI[1]	13.70
Military Lands	83,101	Land Ownership	ESRI[1]	1.02
Bureau of Land Management (BLM) Lands	614,117	Land Ownership	ESRI[1]	7.60
Sage Grouse	239,645	Ecological	BLM	3.14
Dixie Valley Toad	2.3	Ecological	U.S. Geological Survey	-
Teihm Buckwheat	0.052	Ecological	U.S. Fish and Wildlife Survey	-

2. reV Geothermal Development and Code Repository

We developed a novel geothermal generation module for reV that provides access to the functionalities that were previously ported to SAM from the GETEM module, enabling users to execute GETEM effectively and efficiently across a large spatial extent. Moreover, the economic evaluation, land availability accounting, land characterization capabilities, and transmission cost calculation features of reV are now readily available for geothermal resource analysis, with the same extent of application as for other renewable technologies (i.e., wind and solar).

2.1 Accounting for Depth

The addition of a depth dimension is a unique feature of geothermal resource data, and one that reV had not explicitly handled previously. Nonetheless, the structure of this data is similar to wind resource data for various hub heights, and as such, we have handled the depth-dependence of geothermal resource data in a manner similar to wind speed data hub height. Specifically, reV has the capability to either model all sites at a single depth or to pull temperature data for various depths on a site-by-site basis. This approach provides a high degree of flexibility when generating geothermal supply curves, enabling users to tailor analyses to suit their specific needs.

2.2 Generation

An important note here is that PySAM allows for calling these GETEM calculations for all the locations for which we have geothermal resource estimations. A typical reV run begins with the generation module. In this module, every point in the geothermal input data is filtered (described

[1] https://www.arcgis.com/home/item.html?id=5e92f2e0930848faa40480bcb4fdc44e

in Section 1.3.3) and then passed through PySAM/GETEM. At each location based on the geothermal resource data (see Sections 1.3.1-1.3.3) reV takes the following inputs:

- Total resource potential
- Resource temperature
- Resource depth
- Plant output

The total number of generation points evaluated is dataset dependent and is given in Table 1. For each point, the following are output:

- Total annual energy generated
- Capacity factor
- Resource LCOE

These values are calculated and stored in an output file.

Most of our geothermal plant technology assumptions align with the default technology values set in the SAM software interface (Figure 5). However, as advised by the SAM developers, we increased the "Ratio of Injection Wells to Production Wells" from the EGS default value of 0.5 to 0.75 (0.75 is default for hydrothermal). Therefore, increasing this for EGS may result in higher lifetime operation and maintenance costs as it reflects the ratio of injected fluid versus produced fluid. The latter value is consistent with earlier versions of GETEM and yields fewer errors when running on our resource data. In addition, when executing reV generation for EGS, we set the "plant design temperature" to be the lower of 1) the default value (200°C) and 2) the resource temperature. This extra step ensures that the EGS plant design temperature never exceeds the resource temperature, allowing execution to proceed without any errors.

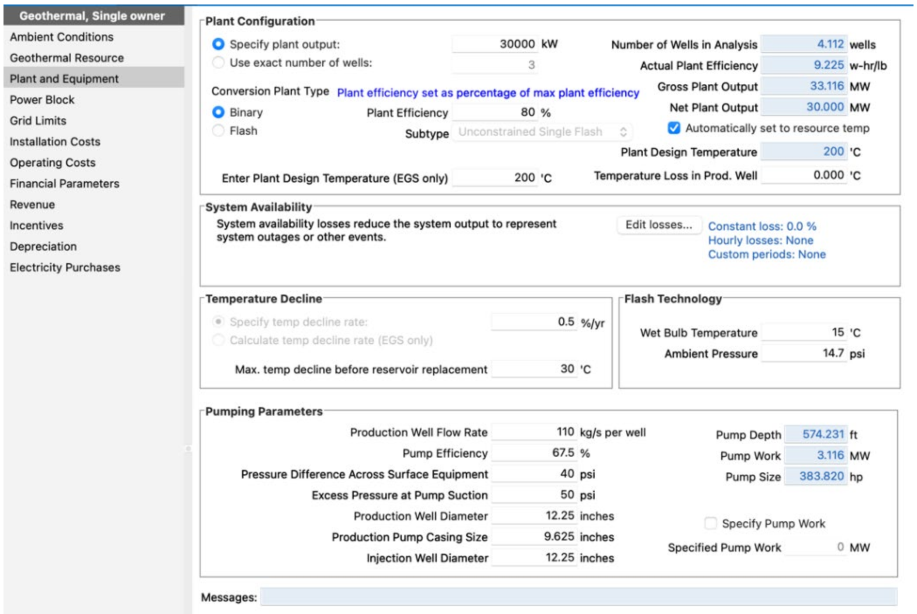

Figure 5: SAM software interface, showing the input parameters needed for one run of SAM/GETEM. This is done seamlessly for many locations by the reV geothermal module.

The LCOE is calculated via user inputs for capital cost, fixed operating cost, variable operating cost, and fixed charge rate. For the results presented in this paper, we used cost values from the 2023 Annual Technology Baseline (ATB) (NREL, 2023). The values are summarized in Table 3.

Table 3: Financial options used as input for two geothermal technologies (GETEM inputs)

Scenario	ATB Capital Cost ($/kW)	Adjusted Capital Cost* ($/kW)	Fixed Operating Cost ($/kW)	Variable Operating Cost ($/kW)	Fixed Charge Rate (%)
Hydrothermal Binary	4,828	4,521.92	129	0	6.348
EGS Binary	5,791	5,417.59	254	0	6.348

*Overnight capital cost minus drilling costs for default plant, calculated using GETEM depth-dependent cost curve

To account for depth-dependent drilling costs, we calculated the drilling costs associated with the sample plant assumed by the 2023 ATB using GETEM depth cost curves (NREL, 2023). Specifically, we assumed the default ("Ideal") cost curve with a vertical open hole well type and a large well diameter. The drilling costs were subtracted from the base ATB capital costs. reV then calculates depth-dependent drilling costs based on the number of wells required at each site. The depth-dependent drill costs used in this work are summarized in Table 4.

Table 4: "Ideal" Cost curve calculations

These calculations are done as a preprocessing step until GETEM calculations are exposed in PySAM.

Depth (km)	Drilling Cost per Well ($)
2.5	2,391,703
3.5	3,130,258
4.5	3,864,018
5.5	4,592,983

The number of wells at each site was determined using internal SAM/GETEM calculations. Specifically, SAM/GETEM internally determined the number of production wells required to obtain the desired nameplate capacity ("Plant Output") at each location. By default, SAM/GETEM allows 50% of confirmation wells to be used as production wells, so the number of production wells required to be drilled is typically decreased by 2. We allow reV to override this default behavior so that users can set the number of confirmations wells to be recycled into production wells. Note that costs for exploration/confirmation wells were not modeled as part of this analysis, so the conversion from confirmation to production wells serves purely as a cost reduction. The final number of wells per site is the total number of production wells determined by SAM/GETEM minus the number of confirmation wells that can be used as production wells (0 or 2) plus the number of injection wells. For example, at a site requiring 4 production wells, the total number of wells was determined to be 4 (production) – 2 (confirmation) + 3 (injection) = 5 total wells.

An important note here is that some of the SAM/GETEM functionality has not been completely exposed in the PySAM version, thereby limiting the capabilities of this analysis. Once the GETEM drilling cost calculator is exposed, results may change slightly over this reV preprocessing that has been implemented.

2.3 Variable Power Density

In conventional practice, reV capacity potential assessment involves a constant power density assumption. However, due to the significant spatial variability of a conventional geothermal resource, which is the main factor driving the capacity calculation, we have incorporated spatial variability into the geothermal power density estimation. To determine the power density value at a particular site, we divide the nameplate capacity by the area of the resource cell.

For the SMU temperature data (Blackwell et al., 2011), this methodology is analogous to using the exponential relationship described in Section 1.3.1 and the resource temperature to estimate the power density. The variable power density is used to calculate the capacity potential at each site after accounting for the area left over after geothermal technical exclusions. For the USGS heat flow data (DeAngelo et al., 2022), it is given in milliWatts/m^2, therefore the capacity is calculated by multiplying the area represented by the datapoint (250 m x 250 m).

2.4 Supply Curve

reV geothermal supply curves are computed in the same manner as wind or solar supply curves. Specifically, 90-m pixels within the exclusion layers, outlined in Section 1.3, are removed from consideration before an aggregation is applied to the grid. To be consistent with wind and solar supply curves, an aggregation factor of 128 was used for the results presented in this work, yielding supply curve cells with a maximum unexcluded area of 132.71 km^2. The area left over after exclusions is computed for each supply curve cell, which is then used to calculate the total capacity for that point using the aggregate variable power density. Other outputs, such as LCOE and mean capacity factor, are calculated in a similar manner (aggregated over the non-excluded 90-m pixels).

2.5 Coupling with Transmission

After computing the aggregate reV geothermal supply curve points, we compute the cost of connecting the resulting capacity to the electrical grid (Lopez et al., 2021). Here, we briefly summarize the procedure. We begin by computing the total cost of building a new spur line (or generation tie line) from the hypothetical geothermal plant at the center of the supply curve cell to the nearest existing substation (within the same state). To do this, we compute the least-cost path within a cost layer that accounts for factors such as variable Independent System Operator (ISO) costs and terrain slope. The total distance of the spur line path is used to compute the cost of the new line, along with any additional overhead costs of connecting the new line to the substation. We optimize across three different spur line ratings (69, 138, and 230 kilovolts) and ensure that the built-out line has enough capacity to support the generation capacity of the geothermal plant represented by the supply curve cell. Multiple parallel spur lines are allowed. The cheapest spur line configuration for each supply curve point is determined and recorded.

Once the cost of building a new spur line from the geothermal plant to the closest existing substation is determined, we calculate the associated network upgrade costs for that plant. These costs account for the increase in the transmission capacity between the connected substation and the main network node in the balancing area. Network upgrade costs are determined by calculating the distance along existing transmission lines to the main network node and are assumed to be 50% of the cost of a new greenfield transmission of the same voltage as the existing transmission lines along the same path. The 50% heuristic represents cost for reconductoring or increasing the number of circuits along those lines. The computed network upgrade costs for each supply curve point are determined and recorded.

The spur line and network upgrade costs are added together and converted to a levelized cost of transmission (LCOT) value using the fixed charge rate (FCR) and annual generation calculated during the generation step (Section 2.2) for each supply curve point. The LCOT is added to the aggregated LCOE value (Section 2.4) to obtain a total LCOE value.

3.0 Proof of Concept Supply Curves

In this section we present preliminary supply curves in the form of total capacity and LCOE and LCOT maps to represent the new functionality built in the reV geothermal module; however, we emphasize that the resulting capacity and LCOE values should only be considered relative to the limited sensitivity runs presented here and not as absolute or final estimates. This caveat is due to the uncertain and highly uninformed nature of the geothermal resource potential data at the national scale. The SMU derived capacity can be thought of as an upper bound capacity estimate (given the exponential curve used to convert to power density), and the USGS heat flow can be considered a very conservative capacity estimate, given its removal of outliers.

3.1 Supply Curve Assumptions/Parameters

Summary of supply curve assumptions and parameters:

- 128 aggregation factor from 90-m pixels = max area of 132.71 km^2
- Variable power density determined by geothermal resource estimates (Table 1)
- Military and Ecological exclusions (as shown in Table 2)
- Two types of drilling cost curves
    - ATB: Flat rate; assumes 1.5-km depth, 175°C resource, and 30-MW plant
    - Preprocessing step to mimic cost curve calculator not yet in PySAM/GETEM
- Costs include spur line transmission to closest transmission feature and relevant network upgrade costs
- LCOE calculated based on energy production under a 6.348% for both hydrothermal binary and EGS binary FCR assumption and includes LCOT

We present five proof of concept reV geothermal results in Table 5; since comparisons are made between the SMU and USGS data, the result columns in blue to the right only compare total capacity and LCOE metrics within the same area covered by the USGS heat flow map (Figure 3). The first three scenarios use the SMU temperatures at 3.5-km depth with the exponential relationship to megawatts. The first scenario uses the ATB well costs (the only available model within PySAM/GETEM), while the second utilizes the preprocessing step to include drilling costs for 3.5 km. Therefore, the total capacity is the same (1,127.64 GW), but the LCOE is more expensive since deeper well costs that match the temperature depth are used ($76.04/MW). The third scenario scales the megawatts of the first two scenarios by 10%, as a way of acknowledging the potential overestimation of the exponential (Equation 2). Total capacity scales exactly by 10%, and LCOE increases by 13% ($86.06/MW) over scenario #2. Scenario #4 uses the USGS heat flow and drill costs for 3.5 km (same as scenario #2). The capacity is less than 3% of the SMU derived capacity at 29.93 GW, and the most expensive LCOE which 1.47 times greater than scenario 2 ($111.85/MW). Lastly, an EGS scenario is run using the SMU temperatures and cost curve both for 4.5-km depth, resulting in both the greatest capacity and an LCOE: 2,005.03 GW and $86.14/MW, respectively. A deeper discussion of these results is presented in Section 4.

Table 5: Preliminary reV geothermal results including four hydrothermal and one EGS run, and two geothermal resource data sources

Scenario	Resource Data	Geothermal Technology	Well Costs	Total Number of Generation Points Across CONUS	Developable Area Within Great Basin (Sq Km)	Total Capacity Within Great Basin (GW)	Median LCOE Within Great Basin ($/MW)*
#1 Hydrothermal Binary SMU Exponential ATB Cost	SMU Temp at Depth (3.5 km)	Hydrothermal (Binary/3.5 km	ATB 1.5 km	319,907	396,490	1,127.64	68.94
#2 Hydrothermal Binary SMU Exponential ATB+Depth Cost	SMU Temp at Depth (3.5 km)	Hydrothermal (Binary/3.5 km)	GETEM Depth Cost Curve	319,907	396,490	1,127.64	76.04 (n_{conf}= 0) 73.92 (n_{conf} = 2)
#3 Scaled Resource of #2 by 10%	SMU Temp at Depth (3.5 km)	Hydrothermal (Binary/3.5 km)	GETEM Depth Cost Curve	319,907	396,490	112.76	86.06 (n_{conf} = 0)
#4 Hydrothermal Binary USGS 2022 ATB+Depth Cost	2022 USGS Heat Flow [milliWatts/m^2] (Western U.S.)	Hydrothermal (Binary/3.5 km)	GETEM Depth Cost Curve	8,902,434	377,572	29.93	111.85 (n_{conf} = 0)
#5 EGS ATB	SMU Temp at Depth (4.5 km)	EGS (4.5 km)	GETEM Depth Cost Curve	520,216	417,715	2,005.03	86.14 (n_{conf} = 0) 85.70 (n_{conf} = 2)

* *Values reported for n_{conf} =0 confirmation wells converted to production wells and n_{conf} =2 confirmation wells converted to production wells (the SAM default) when capacities are large enough.*

For the scenarios in Table 5, we override the default behavior of the confirmation wells being reused as production wells, except for scenarios #2 and #5, which have large enough capacities to require multiple production wells. In those cases, LCOE value for both 0 and 2 confirmation wells converted to production wells are given. As described in Section 2.2, we set the ratio of injection to production wells to 75%.

The spatial results of scenario #2 (hydrothermal at 3.5-km depth) and scenario #5 (EGS at 4.5-km depth) are shown in Figure 6. Recall that areas with temperatures less than 120°C were excluded.

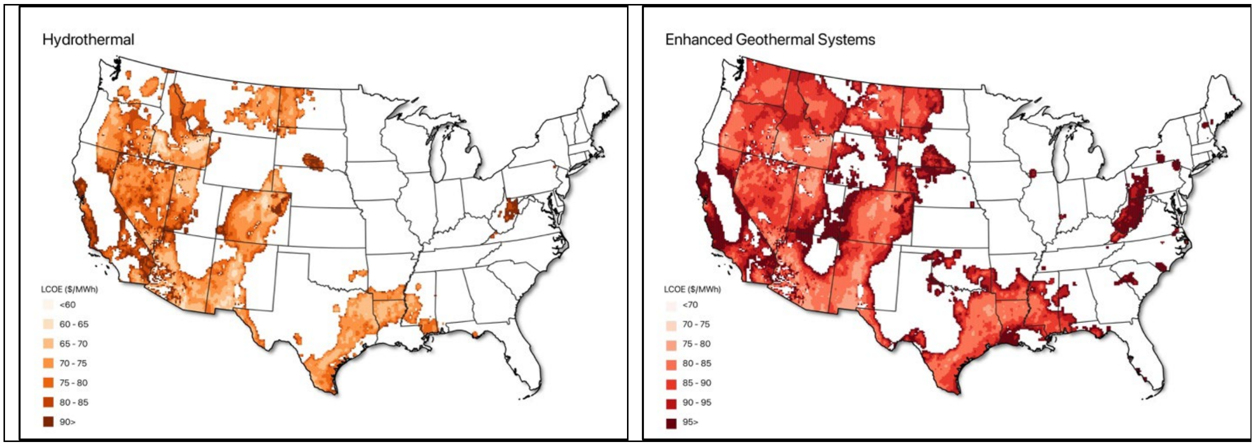

Figure 6: LCOE maps (inclusive of LCOT). Left: Hydrothermal at 3.5-km depth (scenario #2); Right: EGS at 4.5-km depth (scenario #5); note difference in scale (max 90 on left, 95 on right)

One of the benefits of reV geothermal is its spatially exhaustive calculations of intersections of the resource with the grid. Figure 7 shows the LCOT for the same scenarios of Figure 6. LCOT varies greatly given geothermal plant capacities and spur line routing constraints (Lopez et al., 2021).

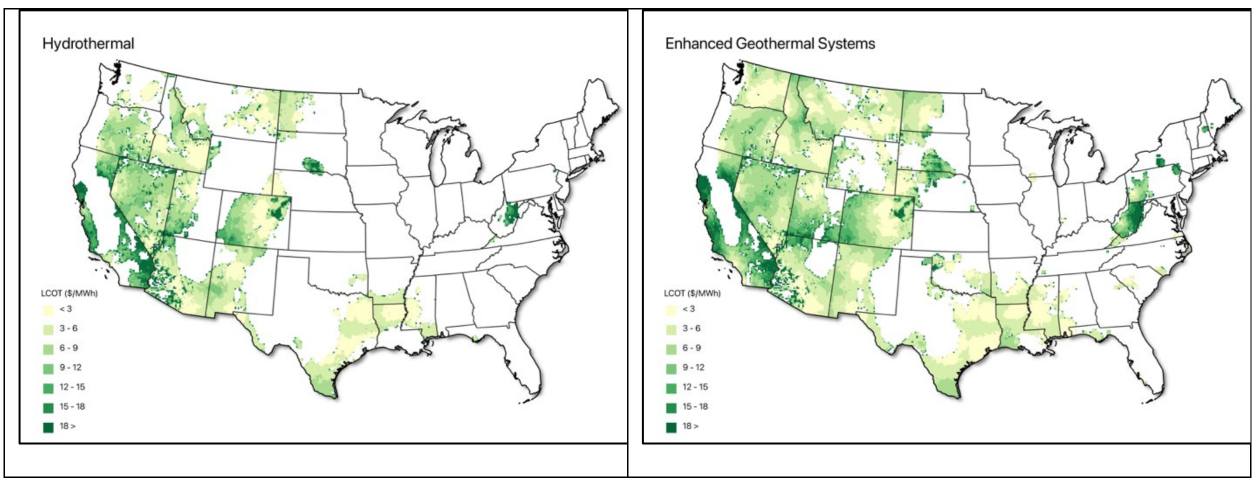

Figure 7: LCOT maps. Left: Hydrothermal at 3.5-km depth (scenario #2); Right: EGS at 4.5-km depth (scenario #5). Same scale

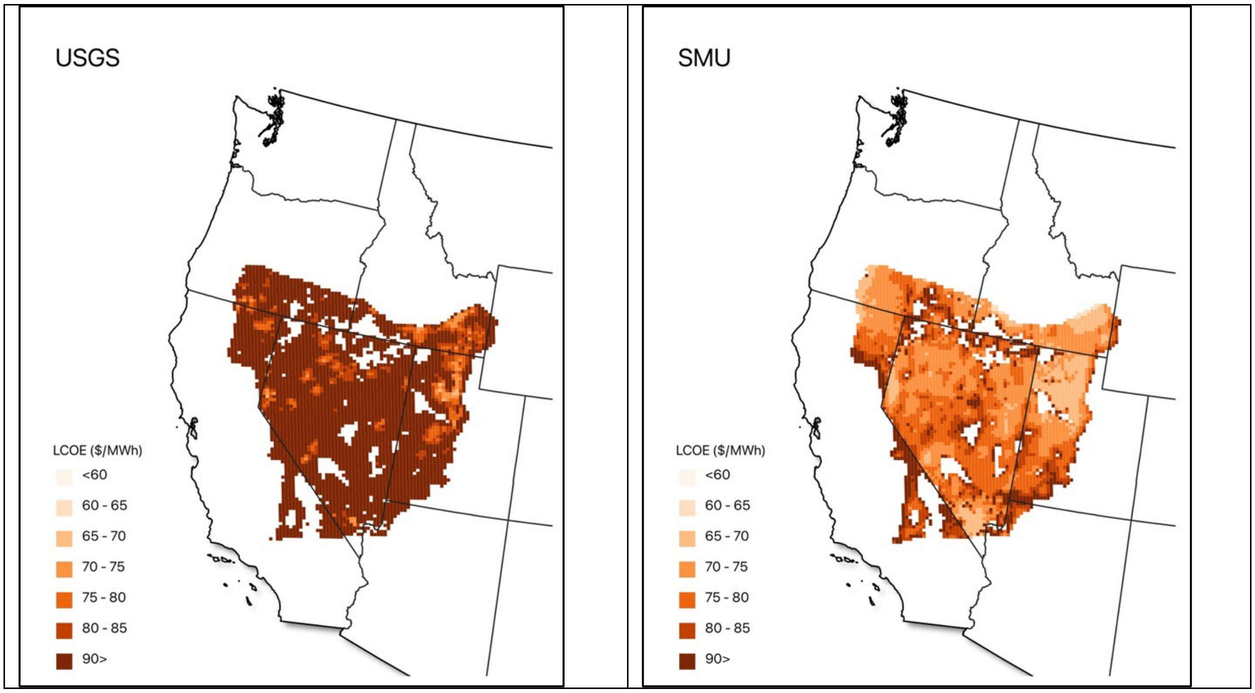

Figure 8: LCOE maps inclusive of LCOT (Left: USGS Binary; Right: SMU Binary)

Figure 8 compares the LCOE maps for the USGS heat flows (scenario #4, median LCOE $111.85/MW) and the SMU temperatures-derived capacity (scenario #2, median LCOE $76.04/MW). The USGS heat flows are two orders of magnitude smaller than the calculated megawatts from the SMU temperatures. Therefore, we see that the LCOE values are higher throughout the Great Basin region versus the SMU-derived values. However, the advantage of using reV is seeing spatially where the LCOE is lowest given the location of the grid; in the USGS case, we can where the LCOE values are lowest (≤$110), which coincides with interstate 80 and the main grid infrastructure in Northern Nevada.

3.2 Observed Versus Calculated Capacity and Temperature Plots

To understand and begin to quantify the reliability the geothermal resource data, we plotted co-located comparisons to illustrate:

1. The observed nameplate capacity of 25 operating geothermal plants versus co-located:
    A. Exponential of SMU temperatures (Figure 9) [MW]
    B. USGS interpolated heat flow (Figure 10) [MW]
2. The measured temperatures from 335 locations within the Great Basin versus the SMU-interpolated temperatures (Figure 11) [°C]
3. USGS heat flow versus the exponential of SMU temperatures (Figure 12) [MW]

We recognize these are imperfect comparisons given the scale of the interpolated or calculated data and the variable footprint of geothermal plants. However, this can provide insight into potential bias introduced by the exponential function and general patterns of the two geothermal resource datasets.

Figure 9 shows the observed megawatts from 25 geothermal power plants (Muntean et al., 2022) versus calculated megawatts (that are spatially co-located) using the exponential relationship with the SMU temperatures at 3.5-km depth. Although we caution that the exponential relationship (Equation 2) likely overestimates the resource potential since the relationship is based on only successful plants, Figure 9 reveals a different pattern. Most of the observed megawatts are higher than the calculated. This is likely because the heat flow (and consequently temperature) is relatively ubiquitous in the Great Basin; what differentiates successful fault-based systems are permeability and fluids, which are likely a hyper-localized phenomenon and therefore not captured in the SMU interpolations of temperature.

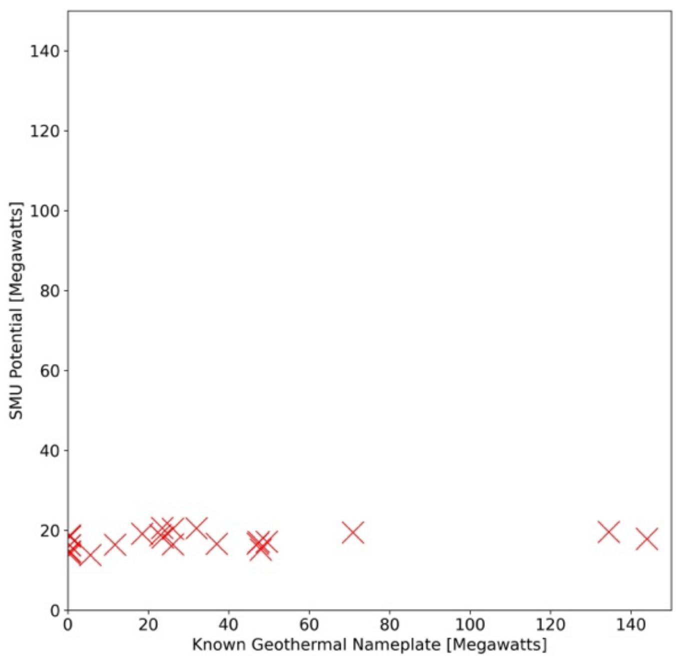

Figure 9: Observed versus calculated megawatts: Observed (x-axis) is nameplate capacity of 25 geothermal plants, and calculated (y-axis) is exponential of the SMU temperatures at 3.5-km depth.

We repeat this comparison of the 25 observed nameplate geothermal plant capacities to the co-located USGS heat flow interpolations in Figure 10. Recall that the intention of the USGS heat flow interpolations is to remove outliers, specifically convection-related hotspots. Therefore, it is expected that the calculated heat flows are much less than the observed. However, they are also at two orders of magnitude less than the SMU-temperature derived calculations, despite summing over 100 USGS points to account for the different spatial resolutions of the two data (Table 1).

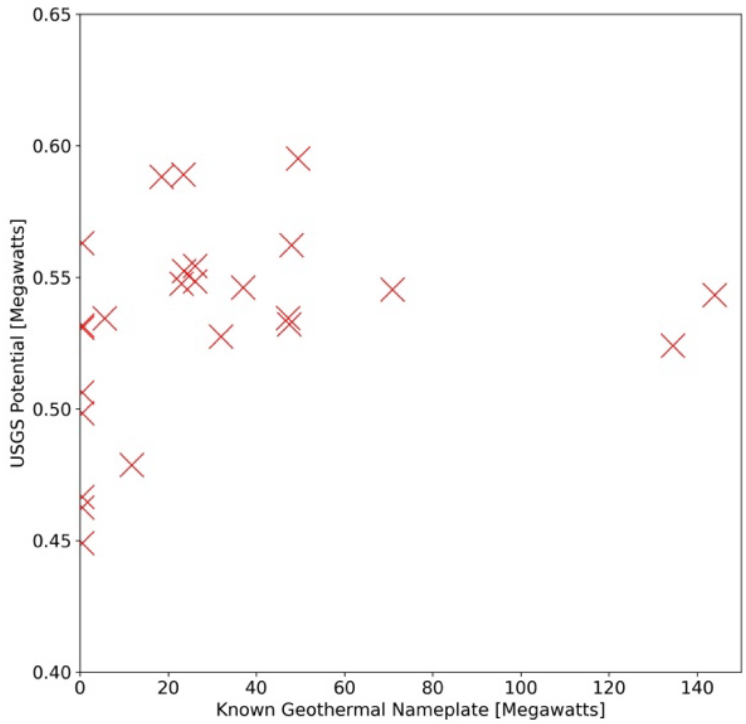

Figure 10: Observed versus calculated megawatts: Observed (x-axis) is nameplate capacity of 25 geothermal plants, and calculated is USGS interpolated heat flow.

Next, in Figure 11, we compare the SMU temperatures (interpolated/calculated) to 335 observed maximum temperatures measured at geothermal sites in the Basin and Range region (Muntean et al., 2022). This comparison can bring insight into the relationship of observed versus calculated temperatures without the added influence of the exponential function. The SMU temperatures are from the interpolated depth of 3.5 km, while the measured temperatures are at variable depths (and depicted by marker size). Not unlike Figure 9, the variability in the observed temperature is much greater than the SMU temperatures. Additionally, the median of SMU is much higher (140°C) versus the observed temperature (47.95°C), however the observed temperatures have a median depth of 236 m, not 3,500 m as are the SMU interpolated temperatures.

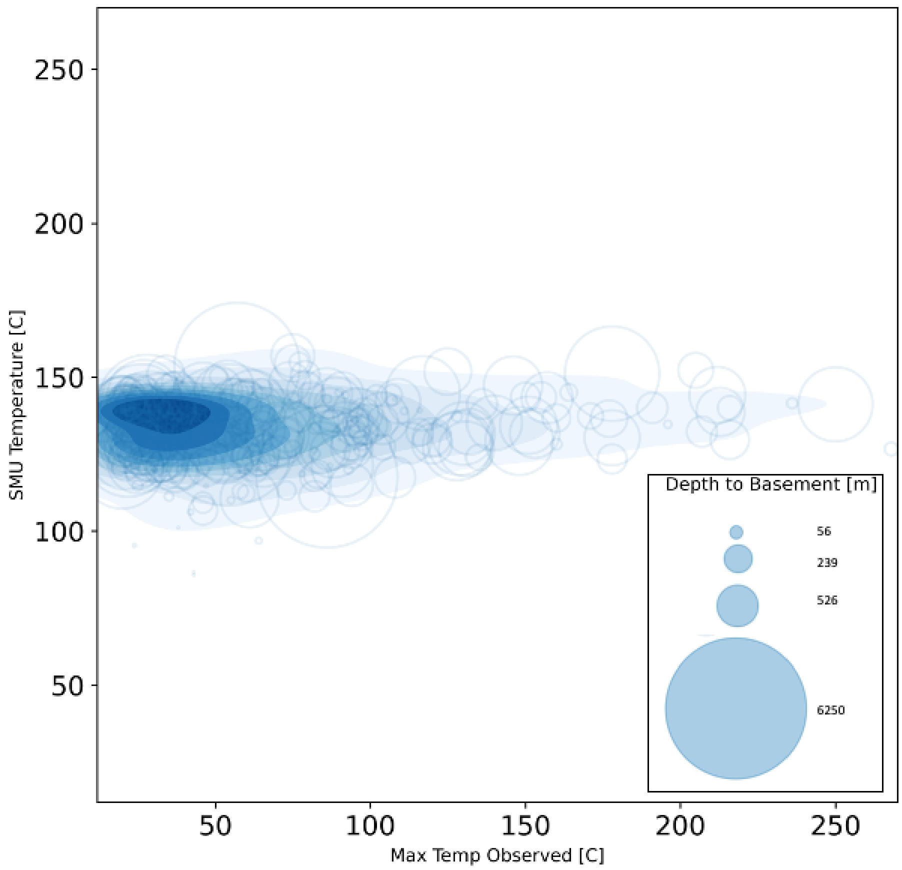

Figure 11: Max observed temperatures at 335 known geothermal sites versus SMU interpolated temperatures (3.5 km); density of measurements is shown in shaded blue. Observed temperatures shown with the circle marker and their depth represented by circle size.

Lastly, we compare the SMU temperature-derived megawatt potential against the USGS smoothed heat flow in Figure 12. In general, the pattern shows that USGS heat flow increases where the exponential of the SMU temperature increases; however, there are two orders of magnitude in the difference.

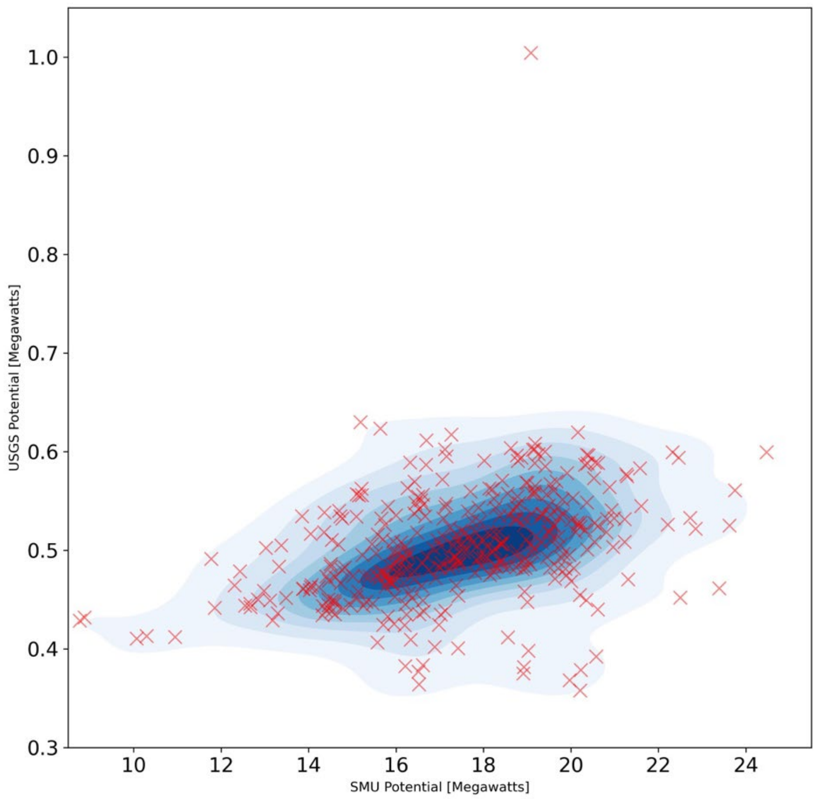

Figure 12: SMU-derived resource potential versus USGS heat flow [MW]

4.0 Discussion and Future Work

The main objective of this project was to develop functionality for geothermal power production in the reV model with a similar level of fidelity as wind and solar. The flexibility and computational efficiency of reV enables rapid national-scale evaluation of hydrothermal and EGS technologies using different geothermal resource datasets, plant configurations, and cost assumptions. We present preliminary geothermal supply curves based on the state-of-the-science geothermal resource data and current functionality provided by SAM/GETEM. While these supply curves demonstrate the high level of uncertainty underlying national geothermal deployment potential, we bound that uncertainty to inform the direction of future resource data modeling needs and functionality in SAM/GETEM to reduce these uncertainty bounds and provide more actionable insights from reV supply curves. The geothermal resource uncertainty also impacts modeling outcomes from ReEDS, thus further necessitating future research into the sensitivity of power system models to geothermal resource uncertainty.

From the scenarios presented in Table 5 and the comparison plots we draw a few important takeaways:

Using the exponential data with the SMU temperature data is conceptually overoptimistic as it assumes temperature will directly convert to megawatts without any inclusion of the need for permeability and fluids for the conventional hydrothermal case.

However, we see in Figure 9 that the calculated megawatts using this exponential is much lower than observed megawatts at 25 operating geothermal power plants. For the Great Basin region (see results columns of Table 5), the average capacity is calculated to be 15 MW for 6.25 km^2 cell size. The average of the listed nameplate capacity for the 25 existing geothermal power plants is 30 MW. For these conventional systems, permeability determines the output, and it varies significantly, impacting how the frequency and spacing of conventional geothermal plants within the Great Basin.

This result further emphasizes the need for new data types to be ingested into reV that characterize the resource. With proxy information on permeability (e.g., faults, fault age, stress), spatial distribution and overlay with critical grid infrastructure will be possible.

Initially, to address the conceptual bias of using the exponential function, we reduced the calculated megawatts by 10% (scenario #3 in Table 5). As expected, the overall capacity is reduced precisely by 10%, and LCOE was observed to increase by 13%. With lower capacity, fewer wells are built out, resulting in lower capital costs.

The USGS dataset can be considered an extreme lower bound given its purpose to remove convective outliers. We propose using other products from USGS, such as their residuals from the same work. The heat flow residuals represent the mismatch of observed/measured heat flows to their interpolated model (calculated and used in this report). Therefore, the positive residuals (where the measured is much greater than what was calculated/interpolated) can represent likely convective hotspots that could represent geothermal potential. The downside is that these residuals only exist where heat flow measurements have been made.

As mentioned previously, the PySAM/GETEM version does not have all functionalities of SAM/GETEM incorporated. The reV geothermal development team imposed preprocessing steps in order to include drilling costs beyond 1.5-km depth. Currently only the ATB cost curve is functional, which assumes 1.5-km depth (scenario #1 in Table 5), resulting in overly optimistic results for larger depths. The results in Table 5 may change once these drilling calculations are fully exposed in PySAM.

These observations lead directly to the proposed future work. The wide variability in the calculated capacities presented here demonstrates how the geothermal resource estimates have a high degree of uncertainty. Uncertainty could be represented within the reV geothermal module through additional resource variables and statistical modeling to quantify and bound the range of resource potential. For example, hydrothermal relies on permeability, and different data types such as fault and stress measurements could be used to inform this variable in conjunction with heat flow. Previous studies, have shown that national estimates of temperature at depth are lower than regional estimates (Augustine et al., 2023); we will consider how to incorporate these types of analyses.

Future work of the reV geothermal module will continue to incorporate PySAM/GETEM. The principal focus will be on improving the representation of geothermal resource and reexamining the assumptions around technology and connection costs that influence the final supply curves. This focus represents the novelty of the project, as it is the first time that resource uncertainty will be modeled in reV.

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