Conventional Hydrothermal Power-Producing Systems of the Great Basin, USA

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ABSTRACT

As part of the update to the electric-grade conventional hydrothermal assessment of the Great Basin, USA, Monte Carlo analyses of identified resources within explored regions will be performed to make estimates of discovered resources and associated uncertainty. Analyses use conditional statistics where estimates are conditioned upon a hydrothermal favorability map, allowing for the likelihood that more resources exist in regions of higher hydrothermal favorability. For these analyses, a dataset of identified hydrothermal systems is compiled, and the new compilation is described herein. Recognizing that a single hydrothermal system may be developed with multiple power plants, and that the hydrothermal upflow zone may be several kilometers across with many measurements characterizing a single hydrothermal system, a procedure was developed and employed to create clusters of points (power plants, measurements, etc.) that are associated with a single system, and a new central point was defined as the best estimator of the center of the hydrothermal system. Hydrothermal systems were uniquely identified by grouping electric-grade hydrothermal measurements and operating power plants within a distance of 10 km. Groups that are >10 km apart are assumed to be different electric-grade hydrothermal systems. While 10 km was used as the threshold, most systems were significantly further apart, and most points within groups were typically within 5 km of each other. A well measurement was considered an electric-grade measurement of a hydrothermal system if it had two properties: a measured temperature of >85 °C and evidence of hydrothermal convection. Other points that were added to the dataset are locations of operating powerplants or locations that have been classified as an electric-grade hydrothermal resource by either the U.S Geological Survey (USGS) or the Great Basin Center for Geothermal Energy. After all points are assigned to systems, new points were computed with the goal of identifying the center of the throat of the hydrothermal upflow zone. If operating powerplants exist for a system, then the arithmetic average of all power plant locations is used. Otherwise, if USGS made an estimate, that location is used. In the absence of both powerplants or USGS estimates, the arithmetic average of all electric-grade measurement locations is used. An example is shown of how these newly compiled locations might be ranked for uncertainty analyses, where higher confidence is assumed if measured temperature is higher and there are many supporting measurements indicating an electric-grade resource. In summary, 28 systems have operating power plants, an additional 78 systems are known identified electric-grade hydrothermal resources, and 99 new systems were identified as probable electric-grade systems with varying levels of confidence. These 205 locations are shown as a function of a recent hydrothermal favorability map, conceptually illustrating the conditional statistics that can be used to make estimates of the undiscovered resources of the Great Basin. An accompanying data release provides summaries of developed capacity by system and USGS estimates of likely total capacity and associated uncertainty.

1. INTRODUCTION

In response to the Energy Act of 2020, the U.S. Geological Survey (USGS) is updating the 2008 provisional assessment of both conventional hydrothermal and Enhanced Geothermal Systems (EGS) electric-grade (>85-90 °C) resources in the Great Basin (extent shown in Fig. 1; Williams and others, 2008a, b; Burns and others, 2025b). Approaches differ between conventional and EGS assessment strategies (Williams and others, 2008b; Williams, 2010), both because the mechanisms differ for conventional and EGS, and because there exist many examples of operating conventional hydrothermal power plants within the Great Basin (Williams and others, 2008b; EIA, 2025; GBCGE, 2025), but few operating commercial EGS plants (Horne and others, 2025). For USGS assessments, when insufficient operating power plant data are available to estimate the statistics of reservoir and power plant performance (e.g., EGS), a provisional assessment is performed, where estimates assume likely continued successful application of early technologies (e.g., Williams and others, 2008a; Burns and others, 2025a). Conversely, when many operating conventional hydrothermal power plants exist within known hydrothermal systems, an understanding of the distribution of size and temperature of geothermal reservoirs has been used for Monte Carlo analyses to estimate the likely total discovered resource and associated uncertainty (e.g., Williams and others 2008a). Statistics of discovered systems from within explored regions are then inferentially applied to unexplored areas to estimate undiscovered resources. Mathematically, the total discovered resource can be estimated as:

$$\widetilde{Q}_{discovered} = \sum_{k}^{N_{discovered}} \widetilde{Q}_k \tag{1}$$

Where $N_{discovered}$ is the total number of discovered systems, $\widetilde{Q}_{discovered}$ is the total power for all discovered resources, Q_k is the power at the k-th system, and the tilde (~) over any variable denotes that this is a random variable. For equation (1), the estimated power for each known hydrothermal system (Q_k) is estimated as a distribution of values, which is why it is represented as a random variable. For the 2008 assessment of conventional electric-grade hydrothermal resources, Williams and others (2008a) present estimates of the distribution of estimated power for each discovered system ($\widetilde{Q}_k$) developed through a Monte Carlo analysis that assumes a distribution of reservoir sizes and initial temperatures for each known system (Williams and others, 2008a). Being the sum of random variables, total power ($\widetilde{Q}_{discovered}$) is also a random variable. Since the 2008 assessment, new conventional hydrothermal systems have been identified and a subset of these have been developed (i.e., $N_{discovered}$ has increased). Herein, the method of identifying and updating the list of known/discovered electric-grade systems is described, and available information about the size of each resource is summarized.
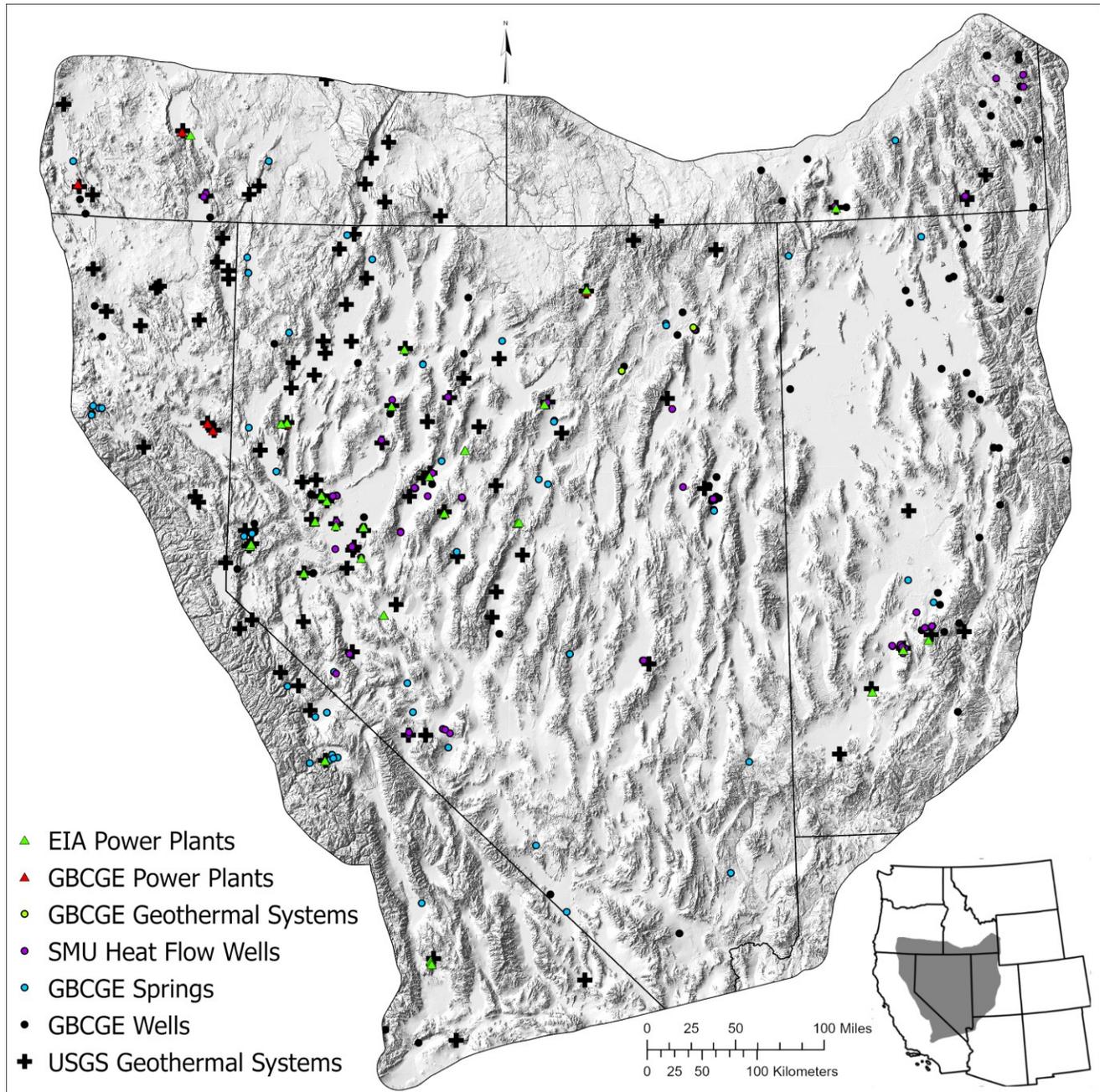

Figure 1: Extent of study area with data used to identify known and probable conventional electric-grade hydrothermal systems (sources described in Section 2.2). Inset shows the western United States. Hillshade is derived from USGS National Atlas (National Atlas of the United States, 2012).

2. METHODS

A conceptual model of an electric-grade hydrothermal system is developed and used as the basis for identifying map locations of discovered systems. Any single system might be developed with multiple power plants, and if power plants are properly sized (i.e., not overbuilt), then the sum of all power plant capacities that tap a single hydrothermal system is less than or equal to the total system capacity. The list of electric-grade hydrothermal systems is constructed by compiling all evidence of electric-grade hydrothermal resources, then simplifying each data cluster into a single point near the geographic center of the cluster.

2.1 Conceptual model of an electric-grade conventional hydrothermal system in the Great Basin

Most conventional hydrothermal systems in the Great Basin are deep circulation systems, though some systems may have a component of heating by rising magma. In a deep circulation system, hot water rises vertically or sub-vertically through conduits created by structurally complex faults where the relative motion has a tensile component that creates the open pathways (e.g., Fig. 2 of Faulds and Hinz (2015)). The flowpath can be complex with dead-end paths and lateral flow through stratigraphic layers (e.g., Figs. 2 and 3 of Siler and Pepin (2021)), so can be conceptualized as a random percolation path, but flow is dominantly vertical from the circulation depth where the water has been heated by conductively supplied heat. This vertical permeability is episodic on a geological timescale, and while the system is flowing, the upflow zone is heated, creating an expanding thermal halo that is a few kilometers in diameter (typically 1-5 km and rarely up to 15 km across according to Fig. 2 of Faulds and Hinz (2015)). The primary controls on whether or not the system creates electric-grade geothermal reservoirs are the thermal gradient and the depth of circulation. Hydraulically, if circulating water can find an easier flowpath, then the water will follow that path, so shallow circulation paths will short-circuit deep paths resulting in lower temperatures in the near subsurface, and this appears to frequently be the case (e.g., DeAngelo et al., 2024). In general, the source of water to the circulation depth is not known, but the flow rate of water in hydrothermal systems is small and discrete compared to regional groundwater flow rates, so from a groundwater perspective, these are small special flowpaths, which is one reason why some systems can be hidden (without surface manifestations) as they are cooled by regional groundwater dilution or shallow lateral flow. Because the narrow upflow path is structurally controlled, the upflow and surrounding halo occupy only a small fraction of the total map area of the Great Basin, and individual clusters of points measuring a single hydrothermal system tend to be within a map distance of 4 to 5 km with an expected maximum of 15 km. Structural paths might also be utilized by rising magma, which brings a heat source to a shallower depth, resulting in anomalously hotter water for shallower circulation paths.

2.2 Compilation of data points that provide evidence of a conventional electric-grade hydrothermal system

The following data were used as evidence of the existence of electric-grade hydrothermal systems:

1) The identified moderate and high temperature geothermal systems used for the 2008 USGS conventional resource assessment of the western US (Williams and others, 2008b; DeAngelo and Williams, 2010);
2) Operating conventional geothermal powerplants from the U.S. Energy Information Administration (EIA; U.S. EIA, 2025) and the Great Basin Center for Geothermal Energy (GBCGE; GBCGE, 2025);
3) A measured temperature or an estimated chalcedony geothermometer temperature (constrained to the case when |charge balance| ≤ 5%) at springs of ≥85 °C (Mlawsky and Ayling, 2020);
4) A measured temperature or an estimated chalcedony geothermometer temperature (with |charge balance| ≤ 5%) of ≥ 85 °C measured in a well, AND the temperature or heat flow is anomalously high, indicating hydrothermal upflow is occurring in the near vicinity (Mlawsky and Ayling, 2020; SMU, 2021, DeAngelo and others, 2022);
5) Geothermal systems with temperature ≥ 85 °C from the 2021 GBCGE dataset (Faulds and others, 2021).

Anomalously high heat flow might be an indicator of hydrothermal circulation, but without a measurement of ≥85 °C (directly or by geothermometer), the system may not be electric-grade. Measured downhole temperatures of ≥85 °C would indicate an electric-grade resource, but without evidence of hydrothermal circulation, the resource would not be classified as a conventional hydrothermal resource (i.e., possibly an EGS resource or other). A measured borehole temperature is assumed to be anomalously high (assumed to be the result of hydrothermal upflow) when measured temperature exceeds the predicted conductive temperature (using Burns and others, 2024b) by a significant amount, defined here as more than the measurement depth times 7.5 °C/km (see example shown in Fig. 6 of Burns and others, 2024a). A measured borehole heat flow is assumed to be anomalously high when the measured heat flow exceeds estimated background conductive heat flow by at least 50 mW/m² (DeAngelo and others, 2022, 2023).

2.3 Identification of electric-grade conventional hydrothermal systems

Data points compiled using methods described in section 2.2 were checked for accurate location (with mislocated entries flagged for removal from location calculations) and subsequently clustered using two rules:

1) If the point is within 10 km distance of other points, it belongs to the same group as the nearest point, allowing a 'chain' of points to be identified, adding any point to the group within 10 km of another point,
2) Points that are greater than 10 km from points in a group cannot belong to that group, so a new group, representing a new hydrothermal system is defined.

These rules are consistent with the observations of Faulds and Hinz (2015) that the hydrothermal upflow zone and surrounding halo are typically <5 km across, but sometimes up to 15 km across. After evaluation of a range of distance thresholds, 10 km was found to be a robust cutoff to efficiently identify groups that adhere to the conceptual model that hydrothermal upflow zones are discrete and relatively sparse compared with the entire map area.

Ultimately, the goal is to create a point that is the best estimate of the geographic center of the hydrothermal upflow zone, recognizing that the disparate datasets do not always agree on the locations of measurements and operating powerplants. The following rules were used:

1) Developed systems: If operating power plants exist, then the geographic center is the best estimator of the permeable throat of the system. The arithmetic average of all power plant locations from all sources is used.

2) Identified (but undeveloped) systems: In the absence of operating powerplants, but USGS made an estimate of the hydrothermal system location, this location is used. If multiple USGS systems exist within 5 km of each other, the average of the locations is used herein with the maximum temperature estimates, and the sum of volume and power production estimates applied the combined system, this resulted in six combined systems from six pairs of systems.

3) Probable systems: In the absence of either of the above, the arithmetic average of all electric-grade measurement locations is used (Section 2.2, criteria 3-5). Because measurements might be in the thermal halo and not in the permeable throat, the average of these locations has inherently lower confidence. Also, confidence that these are electric-grade systems worthy of being developed increases with multiple supporting measurements and higher measured temperature.

An example of how Probable systems can be ranked for consideration of uncertainty is provided below. The example assumes that Rank 1 systems are those with more than one electric-grade measurement and a maximum measured temperature >130 °C. Rank 2 systems are those that are ≥ 130 °C but only one measurement, or between 85 and 130 °C with multiple measurements. Rank 3 are systems defined using only one measurement and having a temperature in the range 85-130 °C. The thresholds chosen herein for the example Ranks are chosen for illustration purposes only, providing the reader an intuition when examining the resulting maps.

Summary points from point clusters implicitly have a range of uncertainties regarding their status as an "electric-grade hydrothermal system". Previous USGS systems (DeAngelo and Williams, 2010) and operating power plants are all high-confidence Identified (includes Developed) systems. All other systems have comparatively lower confidence (Probable systems). For the Probable systems, a cumulative distribution plot was prepared that summarizes the maximum temperature (measured or geothermometer) and the number of points within a cluster, under the assumption that repeat measurements and higher temperatures increase the confidence that an electric-grade resource truly exists at a location.

## 2.4 Summary plots of electric power capacity by system

When USGS estimates (DeAngelo and Williams, 2010) or associated operating powerplants exist for a system, plots are prepared to summarize this information, allowing a rapid comparison of current nameplate capacity with past estimates made by USGS. USGS estimates contain the mean estimate as well as the P95 and P5 estimates, which represent a 95% confidence that the system capacity is at least as large as the P95 value, and only a 5% chance that it will be larger than the P5 value.

3. RESULTS AND DISCUSSION

Within the Great Basin, there are 106 Identified systems (Fig. 2), 28 of which are Developed with operating power plants. Five of these Developed systems were not included in the 2008 USGS dataset, these were derived from power plant locations. An additional 99 systems were identified as Probable new systems (Fig. 2 shows the example ranks: Rank 1 = 13, Rank 2 = 33, and Rank 3 = 53).
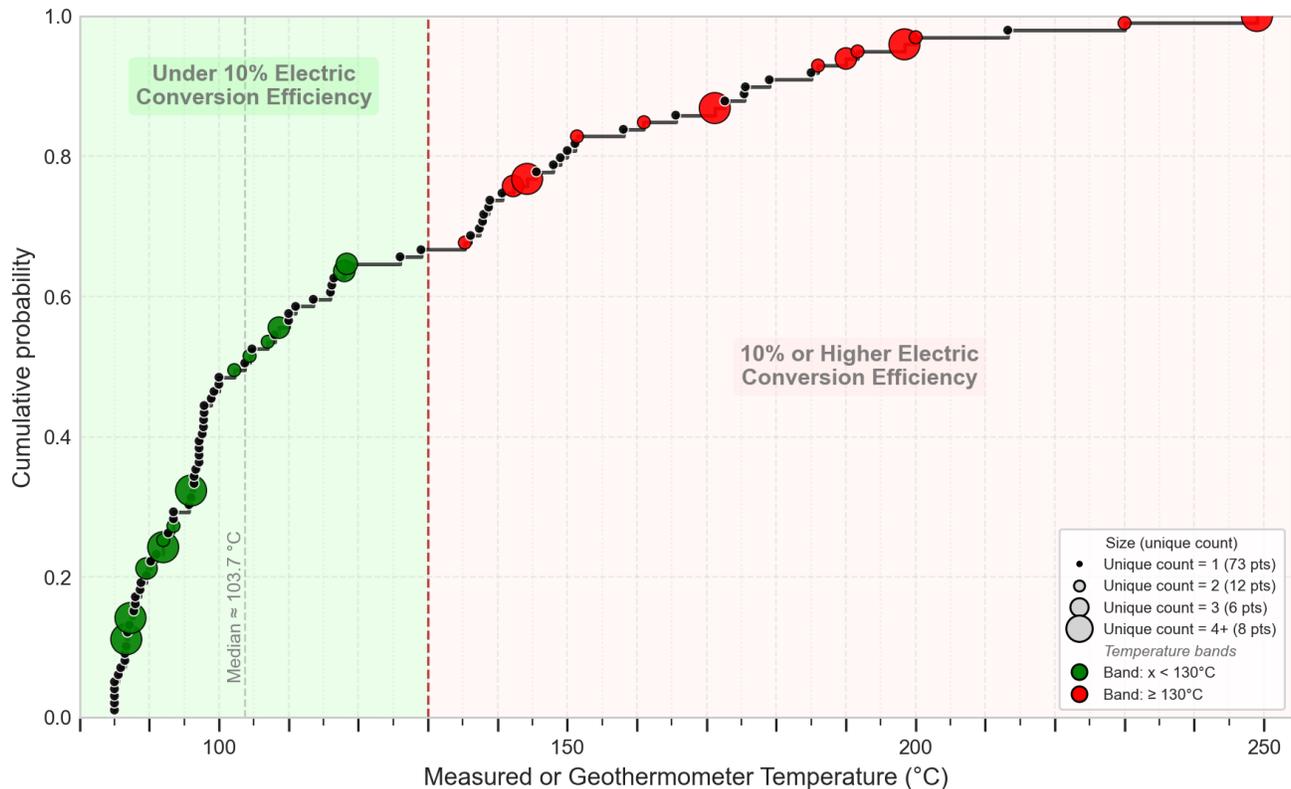
3.1 Map of discovered electric-grade hydrothermal systems

Data were compiled (Section 2.2), then clustered and simplified to a central point for each cluster (Section 2.3) to create a map of 106 Identified and 99 Probable electric-grade conventional hydrothermal systems (Fig. 2). Points are divided into those where confidence is high that a power plant is feasible (black symbols on Fig. 2), and those with evidence of an electric-grade resource that are potentially lower confidence (colored and ranked points on Fig. 2). Point ranking shown here is for illustrative purposes, merely to provide an example of how these data might be used to understand uncertainty during the Monte Carlo analysis of resources. Recall that the overarching goal is to estimate the total number of discovered systems ($N_{discovered}$) so that the total discovered resource can be estimated (Equation 1). A conservative estimate might be that all black symbols and Rank 1 systems are the discovered viable systems, giving $N_{discovered} = 119$. A liberal estimate could be that all symbols are viable systems, giving $N_{discovered} = 205$. Examining the range of these estimates can allow an evaluation of the uncertainty in the final estimate of discovered resources. This particular example assumes that confidence is higher for higher temperature systems and systems with more measurements (ranking rules listed in Section 2.3, with example threshold conditions shown graphically on Fig. 3).
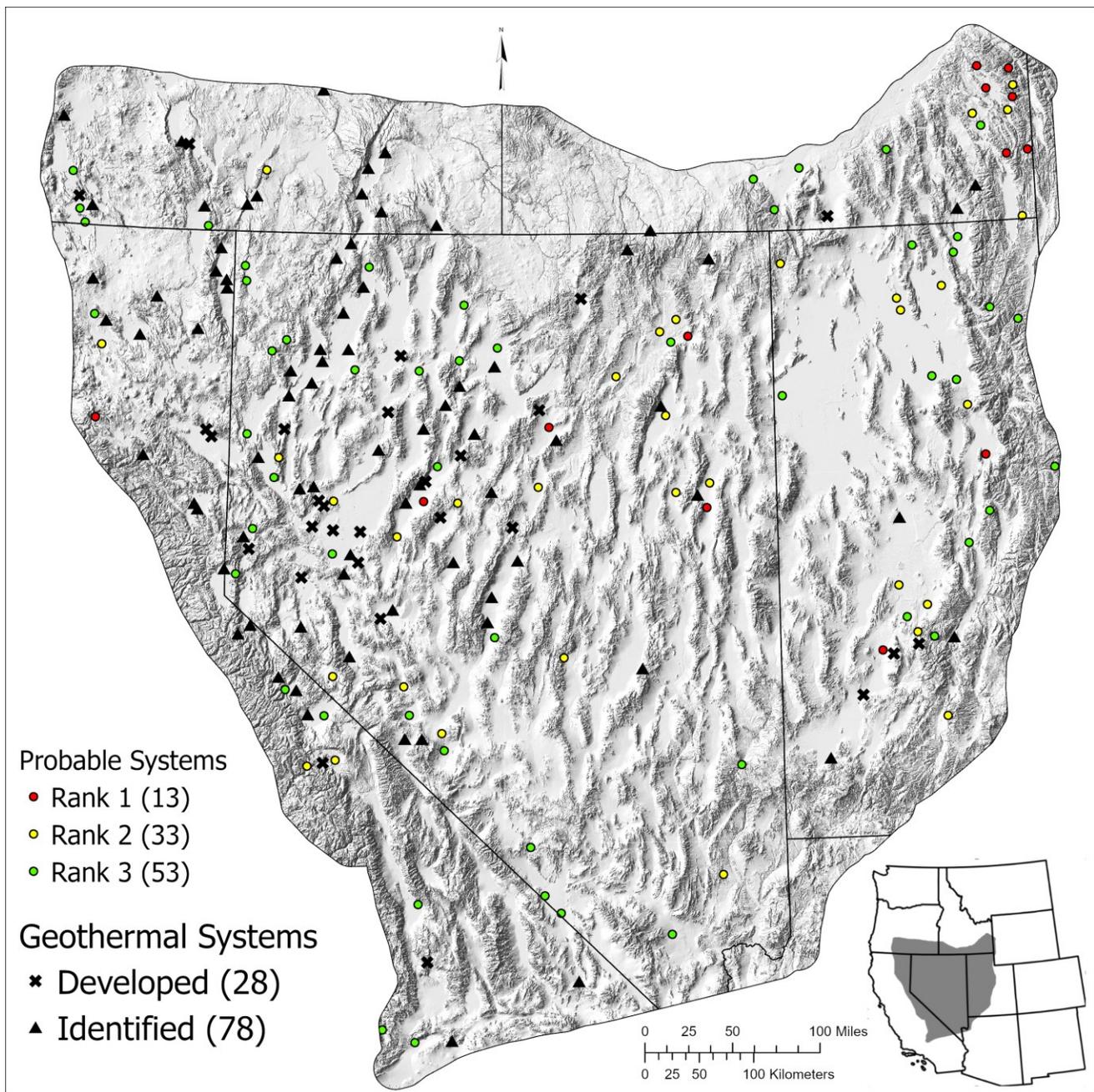
Figure 2: Map of electric-grade conventional hydrothermal systems. Black symbols represent locations of Identified systems, and colored points represent locations of Probable systems having variable evidence of presence of electric-grade hydrothermal resources. Rankings shown here are an example of how data might be used in the future, with rank 1 being highest confidence and rank 3 lowest. Inset shows the western United States. Hillshade is derived from USGS National Atlas (National Atlas of the United States, 2012).

Figure 3: Cumulative distribution function of clusters of Probable systems as a function of maximum temperature (i.e., ranked systems on Figure 2). Size of each point is scaled to the number of nearby measurements used to define the system, with more points corresponding to higher confidence that a resource exists. The vertical line at 130 °C is where heat-to-electricity conversion efficiency increases to ~10% as temperature increases (from the model of Burns and others, 2025). Dependence of rank (Fig. 2) on number of measurements and measured temperature is described in Section 2.3.

3.2 Histograms of power production capacity

For every identified conventional hydrothermal system used for the 2008 USGS conventional electric-power resource assessment of the western US, there are a range of estimates of power production capacity (e.g., Fig. 4). Only 23 of these systems have been developed by installing one or more power plants (Fig. 4). It is expected that installed capacity should be within the bounds of the USGS estimates, unless the resource has not yet been fully developed. A future evaluation of how well USGS estimates match installed capacity for fully developed resources may provide insight into how well the USGS method works, potentially allowing refinement or improvement. For most of these 23 systems, the currently installed nameplate capacity falls within the P95- P5 estimate bounds, and is often quite close to the mean estimate (e.g. Beowawe HS, Blue Mountain, Brady HS, many others). If the 2008 USGS estimates are robust, it would imply that these systems are likely at or near fully developed. Some systems have low installed capacity compared to the 2008 USGS estimates (e.g. Amedee, Humboldt House – Rye Patch, Wendel, others), indicating these systems may be underdeveloped, with the potential for increased capacity in the future. Another possibility is that the USGS estimate is too liberal, and further effort would be needed to understand why (e.g., are there site-specific circumstances that limit power production?). Finally, some systems have installed capacity that far exceeds 2008 USGS mean power production potential estimates, some even exceeding the P5 estimate (e.g. Steamboat Combined System, Tungsten Mountain). Provided that the capacity is sustainable over an engineered lifetime (e.g., 30 years), then the USGS estimate is too conservative for these systems, and an examination of why may result in future improvements to the method. Eighty-three additional histograms are included in the data release (DeAngelo and others, 2026) for: (1) systems that have USGS estimates, but no installed capacity (seventy-eight total), and (2) systems with operating power plants, but no USGS estimates (five total).
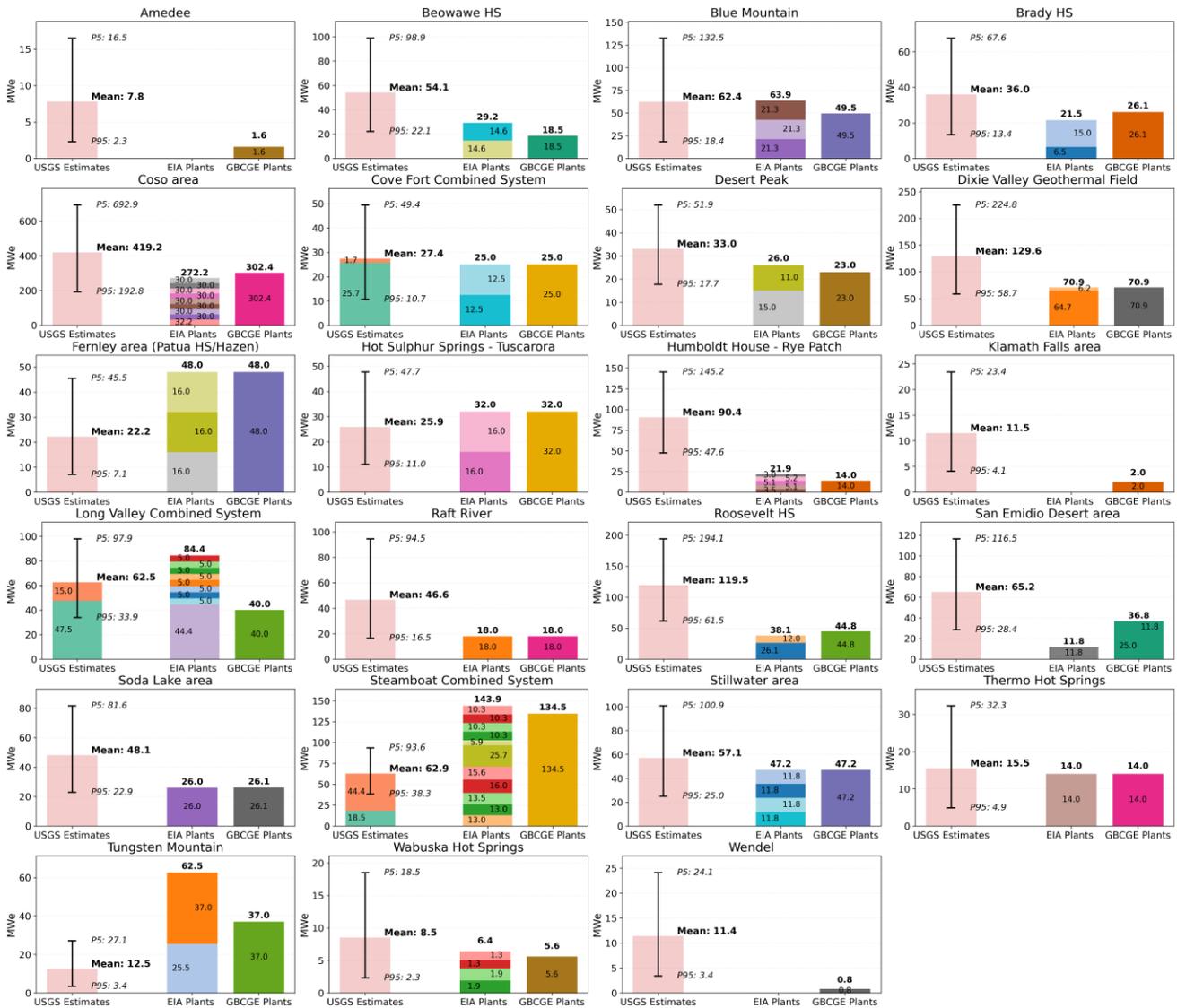
Figure 4: Histograms of the 23 identified systems that have both been developed and that have an estimated range of resource potential summarized by USGS (DeAngelo and Williams, 2010; U.S. EIA, 2025; GBCGE, 2025). The left bar represents USGS estimates for power production capacity in Mwe, showing the P95, mean, and P5 values. The center and right bars represent the nameplate capacities in MWe of power plants associated with Developed systems from EIA and GBCGE power plants, respectively. Stacked bars are shown when the data source divides power capacity into individual powerplants that tap the same hydrothermal system. In the rare case that USGS estimated two separate systems within 5 km distance, the USGS estimates are stacked and the P95 and P5 are the sum of the two systems.

3.3 Example of use of favorability maps with identified and probable systems

Ultimately, the resource assessment will use a favorability map and the identified systems for Monte Carlo analyses to estimate likely undiscovered resource potential and associated uncertainty of estimates. Conceptually, the discovered systems can be used to estimate the density of power-producing systems as a function of favorability for the explored regions, and this understanding can be used to estimate the number of viable systems expected in unexplored regions with similar favorability scores. Once the number of power-producing systems are estimated, the statistics of the USGS estimated systems (Williams and others, 2008b; DeAngelo and Williams, 2010) can be used to estimate the power capacity of the unexplored regions (i.e., the undiscovered resources).

As an example, the favorability map from the Extremely Randomized Trees based model of Mordensky and others (2025) is used, allowing extraction of favorability scores for all Identified and Probable systems. Postulating that the favorability model should perform well for proven resources, Mordensky plotted an area under the curve style plot, where points are ranked in descending order (symbols on Fig. 5 taken from Figure 14 in Mordensky and others (2025), figure for comparison here). Recall that identified system locations are updated here, so favorability scores may differ somewhat due to being at a different location on the favorability map. Also, five new developed systems have been identified herein from power plant locations. These two differences account for the discrepancy between the symbols and the Developed systems line (Fig. 5). The remaining curves show the effect of sequentially adding first the identified but undeveloped

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systems, then the ranked systems. As expected, adding the lower confidence ranked data (e.g., Rank 3) moves the curve down, because these cooler and less certain resources tend to occur in less favorable areas. Because there are powerplants essentially across the entire favorability prediction range, conditional statistics would assign some probability of viable electric-grade systems, even at very low favorability score areas.
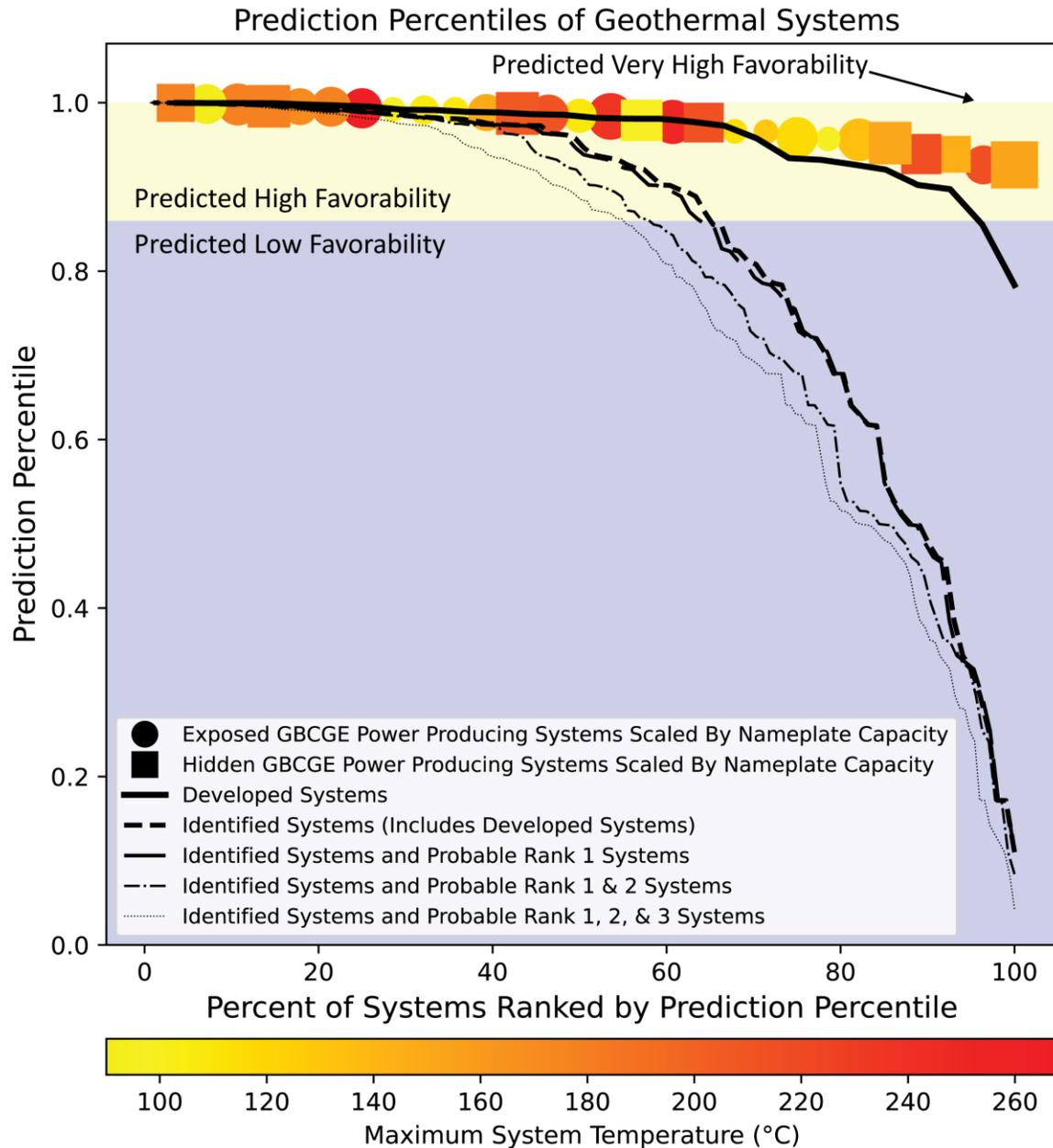
Figure 5: Plot showing the favorability scores for points shown on Figure 2. The favorability map of Mordensky and others (2025) is used, and colored symbols and background coloring are from Mordensky's Figure 14. All other lines show the effect of adding data, and except for the developed systems line, added data are generally of lower confidence. As expected, the new Developed systems curve (created herein) is very similar to the previous Mordensky data (i.e., most of the Developed systems), but as identified but undeveloped systems and the ranked systems are sequentially added, more data points are found in regions of lower predicted favorability.

SUMMARY AND LIMITATIONS

An updated list of identified conventional electric-grade hydrothermal systems is developed. The list of identified systems may or may not include those listed as Probable (Fig. 2), because there is uncertainty that the limited available information is sufficient to ensure that

these systems are viable resources. This uncertainty can be addressed when performing future Monte Carlo analyses to estimate resource potential, and the example ranking (Fig. 2) provides an illustrative example.

The new list makes use of a range of available geothermal data in the Great Basin to provide a more accurate and complete accounting of the locations of discovered systems, the number of possible systems, the current operating capacity of power plants associated with systems, and ways to understand the confidence and/or quality of the systems. Organizing these aspects of the data is a critical step in the goal of providing the best assessment of the conventional resources of the Great Basin. Quantifying the likely total discovered resource and associated uncertainty also allows inference of resources in unexplored areas (i.e., undiscovered resources). The example classification of the systems into rankings that reflect their quality and uncertainty illustrates a possible strategy to account for a range of confidences in the data.

With this range of uncertainties comes certain limitations. While all discovered systems show some evidence of a resource capable of power production, relatively few (28 out of 205) have a developed resource. In the list of identified systems described herein, only 101 systems in the 2008 USGS conventional assessment have estimates for system temperature, volume, and power production potential, each with an estimated range of values to acknowledge uncertainties. Not having been developed or the subject of focused study, the Probable systems have the greatest uncertainty, with some of these systems being defined by a single well or spring observation that could have inaccurate temperature information.

Despite these limitations, several important take-aways are illustrated in Figures 4 and 5. Figure 4 allowed a simple visual inspection of how the 2008 USGS system estimates compare with current-day installed capacity. In most cases, the estimates from the 2008 USGS assessment appeared reasonable, with current nameplate capacity usually within the P95 – P5 estimates, with many showing good agreement with the mean estimate. In a few cases, current production dwarfed production estimates, indicating an underestimation of the power production potential in those systems. Conversely, a few systems appeared underdeveloped, with power production estimates far exceeding nearby installed capacity, indicating that these systems may be well suited for future development. Figure 5 helped to place the results in a context that provided insight into their relative quality and confidence. Our ranking order performed as would be expected if one assumes that the lower ranked systems would fall in areas of lower predicted magnitude of convective upflow. While the data presented herein are only the current best approximation of all discovered systems across the Great Basin, these data vastly improve our understanding of the number, location, quality, and geographic distribution of systems, which in turn, will allow for a better informed and more complete accounting of the discovered and undiscovered resources that will be estimated in the next phase of the assessment.

Additionally, the discovered systems described herein may prove to be a useful new set of training data for models predicting geothermal favorability across the region. These data could have advantages over data that were previously used to train models: systems described herein are more geographically dispersed than existing lists of developed systems, perhaps reducing bias resulting from disproportionate sampling near suspected hydrothermal areas, and allowing for models to identify important patterns in areas not previously examined.

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