PROCEEDINGS, 49th Workshop on Geothermal Reservoir Engineering
Stanford University, Stanford, California, February 12-14, 2024
SGP-TR-227

Preliminary Regional Play Fairway Workflow for the Great Basin Region, USA

Nicole Hart-Wagoner[1], Mark Coolbaugh[1], James E. Faulds[1], Elijah Mlawsky[1], Cary Lindsey[1], Whitney Trainor-Guitton[2], Stephen Brown[3]

[1]Great Basin Center for Geothermal Energy, Nevada Bureau of Mines and Geology, University of Nevada, Reno, NV 89557, USA

[2]National Renewable Energy Laboratory, Golden, CO 80401, USA

[3]Aprovechar Lab L3C, Montpelier, VT, USA

nwagoner@nevada.unr.edu

Keywords: INGENIOUS, play fairway analysis, PFA, feature engineering, geothermal exploration, Great Basin, statistics

ABSTRACT

Play fairway analysis (PFA) is an exploration tool developed in the petroleum industry that has recently been adapted to assess geothermal resource potential and reduce geothermal resource exploration risk. Geothermal exploration risk is particularly high when searching for hidden (or blind) geothermal systems (i.e., systems without surface expressions such as hot springs). Many hidden systems exist in the Great Basin region (GBR) of the western United States, a world-class geothermal province with over 1 GWe installed nameplate capacity. Since 2014, there have been four major Department of Energy funded PFA studies within or adjacent to the GBR, each focused on different parts of the region (the Great Basin interior in Nevada, the Modoc Plateau area of NE California and NW Nevada, the eastern Great Basin in Utah, and Snake River Plain in Idaho). The INnovative Geothermal Exploration through Novel Investigations Of Undiscovered Systems (INGENIOUS) project aims to build on previous PFAs, as well as recent machine learning-based work to improve methodologies/workflows for discovering new, economically viable, hidden systems in the GBR. The INGENIOUS GBR study area encompasses most of Nevada, western Utah, southern Idaho, southeastern Oregon, and easternmost California. A key objective of INGENIOUS is to reduce geothermal exploration risk for hidden geothermal systems by developing a comprehensive play fairway workflow applicable to the entire GBR. Here, we present a preliminary GBR play fairway workflow built from the assessment of 14 newly updated regional geological, geophysical, and geochemical datasets compiled over the GBR study area in Phase I of the INGENIOUS project. The datasets have been analyzed with weights of evidence, logistic regression, and other tools to identify statistically significant relationships between data layers and known geothermal systems. Additionally, feature engineering has been utilized to extract maximum value from the data by developing hybrid predictive features consistent with previously identified physiographic relationships. The identified key predictive feature layers were then statistically integrated using PFA architecture into a preliminary GBR play fairway model. The resulting preliminary geothermal fairway maps improve our understanding of GBR geothermal resources and facilitate identification of potential hidden systems.

1. INTRODUCTION

Geothermal energy is a clean, renewable energy source that has the potential to play a key role in the energy transition away from fossil fuels. The Great Basin region (GBR) in the western United States is a world-class geothermal province. In Nevada alone, the installed geothermal capacity is reported to be 786 MWe (Muntean et al., 2021), and researchers have proposed that GBR geothermal potential could be as high as 30,000 MWe (e.g., Williams et al., 2009). Many of the historical discoveries of conventional hydrothermal systems in the GBR have surface thermal features such as hot springs. However, future geothermal potential is thought to lie mostly in hidden or blind geothermal systems that lack surface thermal features (e.g., Coolbaugh et al., 2007; Faulds et al., 2019). These hidden or blind geothermal systems are more difficult to locate and accordingly carry higher exploration risk. However, the high production rates of some recently discovered hidden geothermal systems, such as McGinness Hills (Nordquist and Delwiche, 2013; Akerley et al., 2019; Muntean et al., 2021) illustrate their discovery value, and consequently there has been an intensive effort to identify and utilize more of these types of systems. The INnovative Geothermal Exploration through Novel Investigations Of Undiscovered Systems (INGENIOUS) project focuses on most of Nevada, western Utah, southern Idaho, southeastern Oregon, and easternmost California (Figure 1). The project aims to facilitate the discovery of new, economically viable hidden geothermal systems in the GBR by integrating new and established techniques to develop a play fairway (PF) workflow that can reduce exploration risk.

PFA is a robust tool that has been utilized in the petroleum industry (e.g., Magoon and Dow, 1994; Peters et al., 2009; Bryant et al., 2012) and has been adapted to assess geothermal resource potential and to reduce exploration risk. In PFA, a set of key geologic characteristics are determined, and the co-occurrence of those characteristics are mapped to determine the probability of identifying a resource within an area of interest (e.g., Weathers et al., 2015). The key geological characteristics of hydrothermal systems are considered to be heat, permeability, and fluid (e.g., Pauling et al., 2023). For hydrothermal systems in the GBR, permeability and heat are the key components assessed in PFA, with permeability generally considered the most important factor.

Since 2014, there have been four major PFA studies within or adjacent to the GBR, each focused on distinct parts of the region, including the Great Basin interior (e.g., Faulds et al., 2021a,b), the Modoc Plateau (e.g., Siler et al., 2017), the eastern Great Basin in Utah (e.g., Wannamaker et al., 2020), and the Snake River Plain (e.g., Shervais et al., 2020). These studies utilized a combination of geological, geophysical, and geochemical data and statistical analyses (e.g., weights of evidence, logistic regression, and fuzzy logic) to estimate heat and permeability components in PFA workflows and generate geothermal favorability maps (e.g., Siler et al., 2017; Wannamaker et al., 2020; Faulds et al., 2021a,b). Additionally, the Nevada machine learning project built on the Nevada PFA results by expanding the datasets and applying machine learning techniques, including supervised probabilistic Bayesian artificial neural networks and unsupervised principal component analysis paired with k-means clustering (e.g., Smith et al., 2023). These projects identified new geothermal prospects and provided insights into GBR geothermal systems. The Nevada play fairway project resulted in discovery of two hidden geothermal systems (Craig et al., 2021; Faulds et al., 2019, 2021b). However, all of these play fairway analyses had limitations such as incomplete datasets, limited training sites, and limited spatial coverage.

Here, we present a preliminary regional PF workflow built from the assessment of 14 newly updated regional geological, geophysical, and geochemical datasets that were compiled over the GBR study area in Phase I of the INGENIOUS project. These datasets have been analyzed through weights of evidence and logistic regression to identify statistically significant relationships between potential feature layers and known geothermal systems. The statistically significant relationships were assessed against probable relationships for typical GBR geothermal systems, given consideration of various geologic constraints. The identified predictive feature layers were statistically evaluated and integrated into a PF model. This preliminary PF workflow was utilized to develop new preliminary predictive geothermal fairway maps and improve our understanding of resource conceptual models in the GBR.

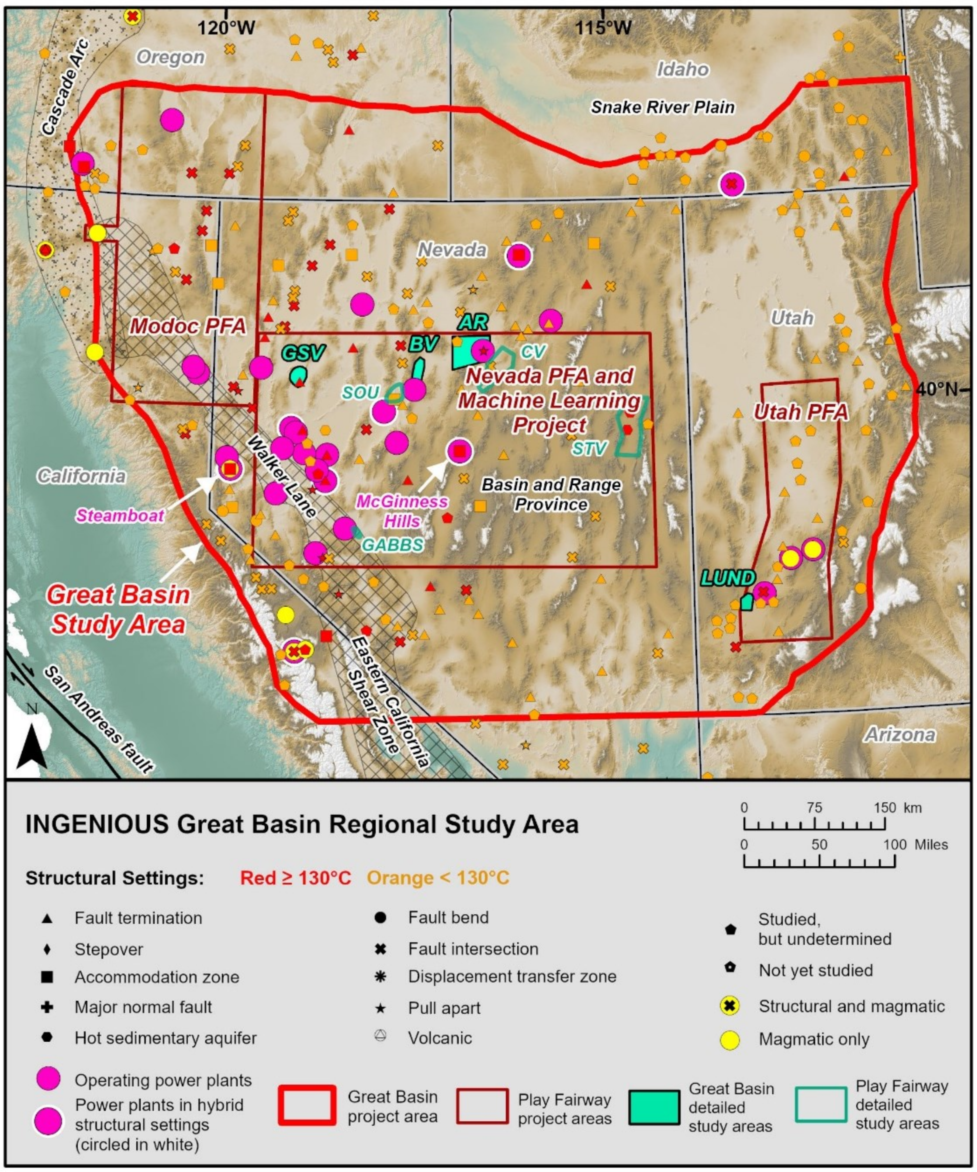

Figure 1: Regional setting of Great Basin study area for the INGENIOUS project, showing locations of known geothermal systems, identified favorable structural settings, previous PF projects (Modoc, Nevada, and Utah), and current detailed study areas (Granite Springs Valley-GSV, Argenta Rise-AR, Buffalo Valley-BV, and Lund). Taken from Faulds and Richards (2023).

2. METHODOLOGY

2.1 INGENIOUS Data

In Phase I of the INGENIOUS project, 14 geoscience datasets were regionally compiled for the 494,269 km² GBR study area (Ayling et al., 2022; Faulds and Richards, 2023). These included six geological data layers: 1) location of Quaternary faults, 2) slip rates on Quaternary faults, 3) age or recency of Quaternary faults, 4) slip and dilation tendency on Quaternary faults, 5) distribution of active and paleo-geothermal features, and 6) distribution of Quaternary volcanic vents and flows. These geologic datasets are critical for evaluating the relationships in the INGENIOUS study area between geothermal favorability and permeability, fluid flow, and reservoir mechanics. Five geophysical datasets were included: 1) gravity data and models 2) magnetic data and models, 3) magnetotelluric (MT) data, 4) geodetic strain rate, and 5) earthquake rate density. These geophysical datasets can be utilized to constrain the subsurface structural and stratigraphic framework, regional strain rates, and local activity on faults. Three heat datasets were included: 1) regional heat flow/temperatures, 2) temperature-geochemical data from wells and springs, and 3) two-meter temperature data. These datasets are vital for understanding the distribution of heat in the subsurface in the GBR and for evaluating the relationship between heat and geothermal favorability in the INGENIOUS study area. All of these INGENIOUS datasets are publicly available on the Geothermal Data Repository at https://gdr.openei.org/submissions/1391.

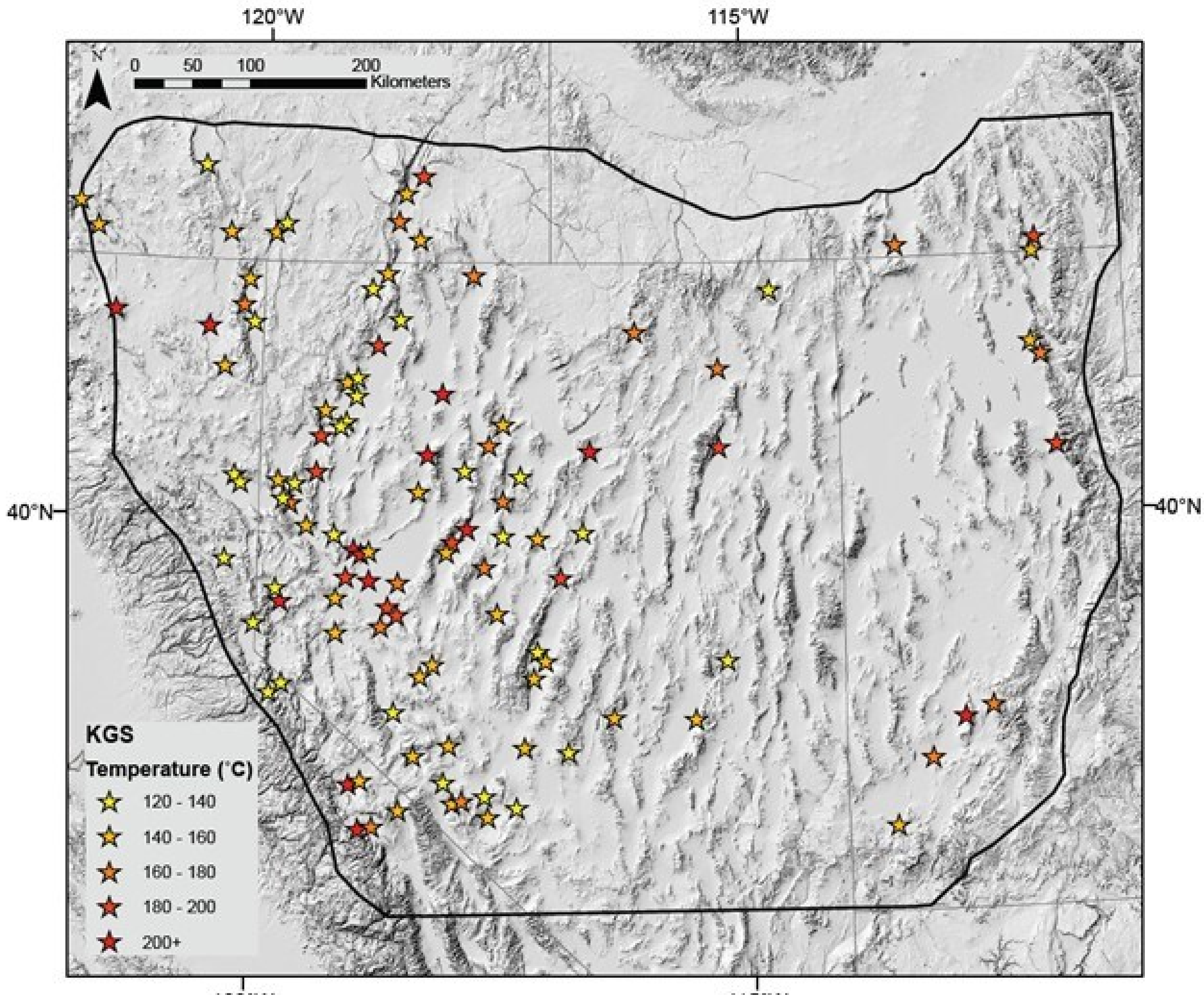

Figure 2: Compiled known geothermal systems (KGS) in the INGENIOUS study area. Selected based on measured or calculated temperatures. From Hart-Wagoner et al. (2023).

2.2 Known Geothermal Systems

A total of 109 known geothermal systems (KGS) with measured or calculated temperatures ≥120˚C in the INGENIOUS study area were identified as training sites for this analysis (Figure 2). These systems are either electricity-producing geothermal systems, identified but undeveloped geothermal systems, or significant convective thermal anomalies based on the presence of hot springs and/or temperature anomalies in wells. A cut-off of 120˚C was utilized because geothermal systems over this temperature are generally considered economical based on current power plant technology and utility costs. These training sites were used as benchmarks to evaluate the predictive capabilities of input datasets.

2.3 Statistical Evaluation Methods

The initial assessment and screening of potential statistical relationships between datasets and known geothermal systems was conducted primarily using weights-of-evidence (WofE). WofE is a statistical method developed based on Bayes' Rule and has been utilized for spatial modeling (Bonham-Carter, 1994; Raines et al., 2000). It is a data-driven method that quantifies the spatial association between a feature and training sites (e.g., Coolbaugh, 2003; DeAngelo, 2019). In past studies, WofE has been utilized to define relationships between datasets and geothermal activity to predict geothermal favorability (e.g., Coolbaugh, 2003; DeAngelo, 2019; Faulds et al., 2021a).

To complete this analysis, datasets are required to be continuous gridded features rather than non-continuous data such as fault segments (lines). Euclidean distance and Euclidean allocation in ArcMap were utilized to generate these continuous grids. Euclidean distance is the distance from each 250 m grid cell in the INGENIOUS study area to the closest feature of interest (e.g., faults), and Euclidean allocation calculates the nearest attribute for each grid cell based on the Euclidean distance. For example, Euclidean allocation calculates the Euclidean distance for each 250 m grid cell to the closest fault and then assigns the attributes of the fault (e.g., recency, slip rate, etc.) to that grid cell. In many cases, the distances were then grouped into bins using a geometric interval (e.g., 125 m, 250 m, 500 m, 1000 m, 2000 m, etc.) to enhance the resolution of the statistical analysis where training sites lie close to major features of interest (e.g., Quaternary faults or volcanic vents), where higher geothermal favorability may be present. This may alleviate the need to use similar datasets on different scales (local versus intermediate versus regional). This process of transforming raw data into a predictive feature that can be used in statistical analyses is considered one type of feature engineering. WofE analysis can then be used to identify statistical relationships between known geothermal systems and input features. These methods were utilized to analyze non-continuous datasets such as Quaternary fault attributes (Hart-Wagoner et al., 2023) and Quaternary volcanic vents.

In this study, WofE analyses were completed using the ArcGIS Spatial Data Modeler Toolbox (Raines et al., 2000). The WofE analysis generates metrics including the positive and negative weights, the contrast (difference between the positive and negative weights), and the student contrast (contrast divided by its standard deviation). High positive weights, low negative weights, and a significant contrast indicate a positive association between the training data (KGS) and the feature layer. Additionally, student contrast is a measure of the confidence in the contrast. These metrics are utilized for both cumulative and categorical WofE analyses. Initial WofE analyses were conducted as cumulative tests. Cumulative WofE is an iterative binary test that identifies the number of training sites that are included as more bins are added to the analysis in each iteration. The cumulative analysis is commonly used to identify thresholds that can be employed to define multiple weights in a categorical WofE analysis. In the categorical test, each bin is tested separately. Smoothed WofE can then be utilized to smooth the relationships defined through categorical WofE analyses, so that the response varies gradationally across the study area, removing the abrupt changes in favorability at category boundaries (e.g., Coolbaugh and Bedell, 2006; DeAngelo et al., 2019). Categorical weights can be determined through WofE and plotted against the data attribute being tested to define the relationship between the categorical weights and the data. A best-fit line can be applied to these data points, and the equation of the line utilized to calculate a smoothed WofE response and grid.

Once initial statistical relationships were verified and documented with WofE, logistic regression was utilized to refine relationships and combine individual feature grids together. Logistic regression is a modified version of linear regression that can predict binary output (presence or absence of a geothermal system) as a probability and does not require conditional independence for predictive data (Wright, 1996). Logistic regression has previously been utilized with WofE to generate predictive geothermal favorability maps (e.g., Coolbaugh, 2003; DeAngelo, 2019; Faulds et al., 2021a). Since the grids and features derived through this research are known not to be completely independent with respect to predicting geothermal potential (e.g., Coolbaugh et al, 2007), logistic regression can be used to combine these layers into a single feature.

Additionally, logistic regression is a linear analysis, and inaccuracies can develop where relationships between the predictive data and training sites are distinctly non-linear, which we find commonly the case for geothermal predictions. Non-linearity issues can be reduced through data transformations and/or data binning wherein each bin defines a restricted range of data with its individually assessed correlations. These adjustments can provide an approximation of linearity within which logistic regression and other statistical tools can work more effectively. In this study, logistic regression was completed using Python, which utilized the logit model developed by statsmodels (Seabold et al., 2010).

3. RESULTS

Quaternary faults and fault attributes, Quaternary volcanic rock, gravity, magnetics, MT, geodetic, earthquake, and heat flow datasets were analyzed using WofE and logistic regression. The preliminary results of these analyses are presented below. For WofE, high positive weights and student contrast over 2 indicate a positive relationship with KGS. For logistic regression, a p-value less than 0.05 indicates the feature is statistically significant. The WofE results are summarized in Figure 3A, and the logistic regression results are summarized in Figure 3B. Results from the WofE and logistic regression analyses were assessed to determine which features to include in the preliminary geothermal play fairway workflow. Features were selected if they showed statistical significance and removed if they did not. In some cases, a layer with statistical significance in WofE, as compared with other layers from that data type through logistic regression, was found to be redundant and was removed.

3.1 Quaternary Faults and Fault Attribute Data

The location, recency, slip rate, and slip and dilation tendency (TSTD) of Quaternary faults were analyzed (Ayling et al., 2022; Siler, 2022). As geothermal favorability is expected to vary as each of these fault attributes varies, Euclidean allocation was utilized to determine statistically significant bins for the values of each of these fault attributes (recency, slip rate, and TSTD). Eulcidean distance was then utilized to generate continuous grids of distance to Quaternary faults for each of the binned fault attributes. Hart-Wagoner et al. (2023)

provided a detailed discussion of the analysis of recency and slip rate, and the same methodology was applied here for TSTD. The distances to Quaternary faults for each of the binned fault attributes were classified in geometric intervals of increasing distance to faults to enhance the resolution of the statistical analysis closer to Quaternary faults, where higher geothermal favorability is expected. Cumulative WofE indicates an approximately linear relationship between positive weights and the log-transformed distance to Quaternary faults for recency, slip rate, and TSTD, with the highest positive weights (2.35 for recency, 2.35 for slip rate, and 2.39 for TSTD) occurring close to faults for each fault attribute. The student contrast values for these high positive weights are 6.52 (recency), 6.11 (slip rate), and 2.36 (TSTD). The relationships between distance to Quaternary faults and positive weights were utilized in a categorical WofE analysis, which was used to define a smoothed WofE relationship for each of the binned fault attributes. The resulting smoothed WofE grids for each binned fault attribute were then combined using logistic regression, producing one grid for each fault attribute (recency, slip rate, and TSTD). These three grids (recency, slip rate, and TSTD) were combined using logistic regression. Logistic regression indicated that the recency and slip rate grids are statistically significant, while the TSTD grid was not. While slip and dilation tendency indicated statistical significance in WofE, if analyzed with recency and slip rate it was no longer considered to contribute significantly to the prediction and was excluded. Therefore, only the recency and slip rate data were utilized to generate a single integrated Quaternary fault layer, which we term a 'super-feature'.

3.2 Quaternary Volcanic Data

Spatial location and lithologic composition were attributes used to define a Quaternary volcanic vents feature (Ayling et al., 2022). Euclidean distance was used to generate separate continuous grids for felsic, intermediate, and mafic Quaternary volcanic vent compositions. The methodology applied here is similar to that developed for the Quaternary fault 'super-feature' (Hart-Wagoner et al., 2023). The distances to the Quaternary volcanic vents of each composition were classified in geometric intervals to enhance the resolution of the statistical analysis closer to Quaternary volcanic vents, where higher geothermal favorability may occur. The cumulative WofE results indicate an approximately linear relationship between positive weights and the log-transformed distance to felsic, intermediate, and mafic volcanic vents, with the highest positive weights (3.15 for felsic vents, 2.75 for intermediate vents, 0.43 for mafic vents) occurring close to vents. The student contrasts for these high positive weights are 5.33 (felsic), 2.72 (intermediate), and 3.15 (mafic). The relationships between distance to volcanic vents and positive weights were utilized in a categorical WofE analysis, which in turn was used to define a smoothed WofE relationship. The resulting smoothed WofE grids for felsic, intermediate, and mafic vent compositions were then combined using logistic regression. As expected, logistic regression suggests a negative relationship between distance to volcanic vents and geothermal favorability. These results also indicated that the felsic and mafic grids are statistically useful for the prediction, whereas the intermediate grid is not. Although intermediate compositions have statistical significance in WofE, if combined with felsic and mafic composition Quaternary volcanic vents, it was no longer considered a statistically significant feature and was excluded. Therefore, only the felsic and mafic volcanic vent data were utilized to generate the Quaternary volcanic vent 'super-feature'.

3.3 Potential Field Geophysical Data

3.3.1 Gravity

The two gravity features analyzed were the isostatic residual gravity anomaly map (Glen et al., 2022) and the horizontal gravity gradient grid. Cumulative WofE analyses indicate a positive association between very low isostatic residual gravity values and the KGS, with the highest positive weight of 2.89 and corresponding student contrast of 2.84. However, there is also a positive association between high gravity gradients and KGS, with the highest positive weight of 2.88 and corresponding student contrast 4.00. If these layers are assessed using logistic regression, only the horizontal gravity gradient is determined to be statistically significant, generating a positive relationship between gravity gradients and geothermal favorability. Therefore, only the horizontal gravity gradient was selected from these two datasets.

3.3.2 Magnetics

The two magnetic features analyzed were the magnetic intensity map (Glen et al., 2022) and the horizontal magnetic gradient grid. Cumulative WofE analyses indicate a positive association between magnetic intensity values or magnetic gradients and the KGS, with very low positive weights and student contrast <2. Assessing these layers using logistic regression suggests that the magnetic anomaly data are close to statistically significant ($p = 0.095$). However, these results indicate a positive relationship between magnetic intensity and geothermal favorability, whereas a correlation with low to intermediate magnetic intensities might be expected due to association with hydrothermally altered rocks (e.g., Glen et al., 2018; Peacock et al., 2018). Therefore, neither the magnetic intensity nor the horizontal magnetic gradient was selected from these datasets.

3.4 MT Depth Slices

Five electrical conductance depth slices estimated from modeling of MT data were analyzed (Peacock and Bedrosian, 2022): near-surface (2-12km), middle crust (12-20km), lower crust (20-50km), upper mantle (50-90km) and mantle (90-200km). Cumulative WofE indicates low positive weights (near-surface: 0.50, middle crust: none with student contrast >2, lower crust: 0.86, upper mantle: none with student contrast >2, mantle: 1.00) and corresponding student contrasts of 2.21 (near-surface), 2.76 (lower crust), 2.65 (mantle). Only the near-surface, lower crust, and mantle depth slices show a weak positive association with KGS. If these layers are assessed using logistic regression, the analysis suggests that the near-surface, middle crust, lower crust, and upper mantle depth slices are statistically significant, and the mantle depth slice is not significant. The results for the near-surface and lower crustal depth slices indicate a positive relationship between conductance values and geothermal favorability, whereas a negative relationship was indicated for the middle crust and upper mantle layers. GBR geothermal systems may be expected to correlate with high conductance values (low resistivity anomalies), which may reflect clay caps, subsurface geothermal brines, or mid to lower crustal magma bodies (e.g., Cumming, 2009; Wannamaker et al., 2011; Munoz 2014; Peacock et al., 2018). Therefore, only the surface and lower crust depth slices were selected from these datasets.

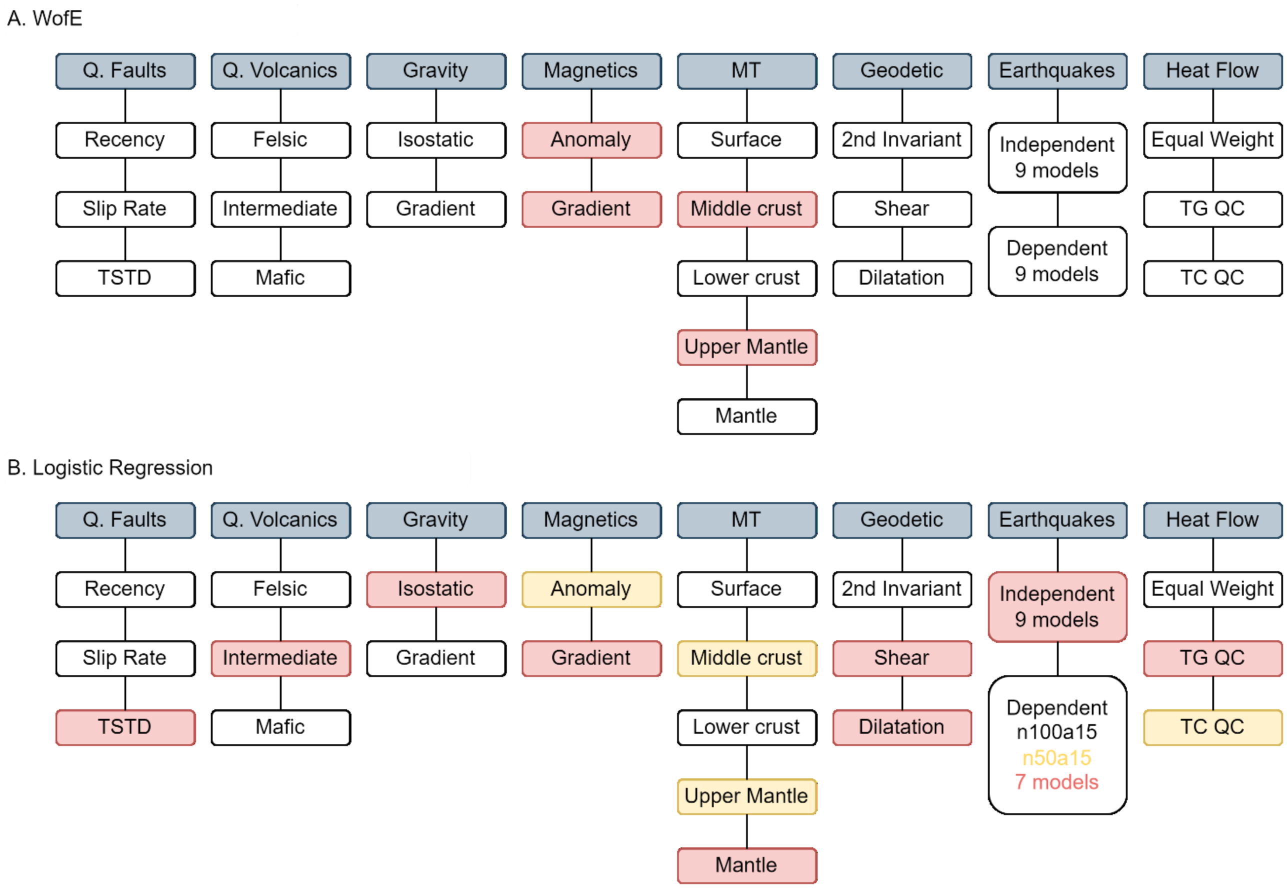

Figure 3: Summary of results from the A) WofE analyses and B) logistic regression analyses. Gray boxes indicate the data type. Red boxes and red text indicate datasets with no statistical significance. Yellow boxes and yellow text indicate datasets with relationships to geothermal favorability opposite of what would be more probable for a typical geothermal system, given consideration of various geologic constraints.

3.5 Geodetic Models

The principal measures of strain derived from the geodetic strain rate model were used to calculate the second invariant, the dilatation rate, and the shear rate (Ayling et al., 2022). These three layers were analyzed by cumulative WofE, which indicated that high values from each of these models have a positive association with KGS, with the highest positive weights of 1.95 (second invariant), 2.18 (shear), 1.77 (dilatation) and corresponding student contrast of 3.34, 2.15, and 3.05, respectively. When these layers are assessed using logistic regression, only the second invariant is statistically significant, and the remaining derivatives are not. Due to the discrepancy between the cumulative WofE and logistic regression results for the different layers, these layers were reassessed to define smoothed WofE relationships, then re-combined. The relationships between the model values and positive weights were utilized in a categorical WofE analysis, which was used to define a smoothed WofE relationships for each layer. The resulting smoothed WofE grids for the second invariant, dilatation rate, and shear rate were combined using logistic regression. Logistic regression still indicated that the second invariant grid was statistically significant, whereas the dilatation and shear rate grids were not. Therefore, only the second invariant was selected from these datasets.

3.6 Earthquake Rate Density Models

Nine models of earthquake rate density were analyzed for both independent (i.e., main shock) and dependent earthquakes (i.e., aftershocks, foreshocks, and swarms) (Ayling et al., 2022). Each of these models has slightly different parameters that affect how the earthquake rate density is interpolated across the GBR. Cumulative WofE indicated that all 18 models have a positive association with KGS, but all have low positive weights. The highest positive weight for the dependent earthquake rate density maps was 1.18 with a corresponding student contrast of 2.04 and 1.19 with a corresponding student contrast of 2.06 for the independent earthquake rate density maps. Assessing these layers using logistic regression shows that only two of the dependent earthquake rate models are statistically significant and the remaining models are not. However, one of these statistically significant models indicate a negative relationship between earthquake rate density and geothermal favorability, whereas high earthquake density may be expected to correlate with geothermal activity as earthquakes would help to keep fractures and faults open for hydrothermal fluid flow (e.g., Micklethwaite and Cox, 2004). Therefore, only one of the dependent earthquake rate models was selected from these datasets. The model chosen has an N value of 100 (N is the nearest number of earthquakes that were considered in generating the earthquake rate density map) and an α value of 0.15 (α is a "declustering parameter" that distinguishes between independent and dependent earthquake events).

3.7 Conductive Heat Flow Models

Three different heat flow models (DeAngelo et al., 2022) were analyzed. One of these models was interpolated by weighting all well data equally regardless of quality, whereas the other two employed measures to de-emphasize well data of lower quality (TG QC: thermal gradient quality code confidence weights, and TC QC: thermal conductivity quality code confidence weights). Cumulative WofE indicate that all three models have a weak positive association with KGS, with very low maximum positive weights (0.22 for equal weight, 0.18 for TG QC, and 0.15 for TC QC) but statistically significant corresponding student contrast (3.37 for equal weight, 2.25 for TG QC, and 2.89 TC QC). Assessing these models using logistic regression shows that the equal weight model and the thermal gradient quality code model are statistically significant, and the thermal conductivity quality code model is not significant. The results for the equal weight model indicated a positive relationship between heat flow and geothermal favorability. However, the logistic regression results for the thermal gradient quality code model indicated a negative relationship between heat flow and geothermal favorability. Since GBR geothermal systems are expected to correlate with high heat flow, only the equal weight heat flow model was selected from these datasets.

4. PRELIMINARY REGIONAL GEOTHERMAL PLAY FAIRWAY WORKFLOW AND FAIRWAY MAP

The statistically significant datasets identified for the preliminary geothermal play fairway workflow included: Quaternary fault super-feature (recency and slip rate), Quaternary volcanic vent composition super-feature (felsic and mafic), horizontal gravity gradient, the near-surface (2-12km) and lower crust (20-50km) conductance depth slices, second invariant of strain rate, dependent earthquake rate model (N = 100, α = 0.15), and the equal-weight heat flow model. In accordance with play fairway methodology, these layers are divided into heat and permeability groups, as discussed below.

4.1 Preliminary Regional Permeability Model

Features selected for permeability components of the preliminary model included the Quaternary fault super-feature, horizontal gravity gradient, second invariant of strain, and dependent earthquake rate density (N = 100, α = 0.15). The Quaternary fault super-feature provides an estimate of permeability related to Quaternary faulting and fault attributes. The horizontal gravity gradient provides an estimate of fault displacement as measured by the density contrast between bedrock and alluvium, which provides insight into subsurface structures that could highlight areas of enhanced permeability. The second invariant of strain provides an overall estimate of the regional strain rate magnitude that could highlight enhanced permeability. Lastly, the dependent earthquake rate model provides an estimate of local activity on faults that could act as active fluid flow paths. In the future, favorable structural settings (FSS) will also be assessed and integrated into the permeability model once the FSS database is finalized.

These four layers were analyzed by logistic regression to develop the regional permeability model (Figure 4). The coefficients calculated from this analysis indicate that the relative importance of these layers from greatest to least is 1) Quaternary fault super-feature, 2) horizontal gravity gradient, 3) the dependent earthquake rate model, and 4) second invariant of strain. The coefficients were then utilized to calculate the preliminary permeability model (Figure 5). This model generally indicates higher favorability in western Nevada and along the Wasatch Front in Utah. Regions of lower favorability are generally located in far western Utah and southwestern Idaho.

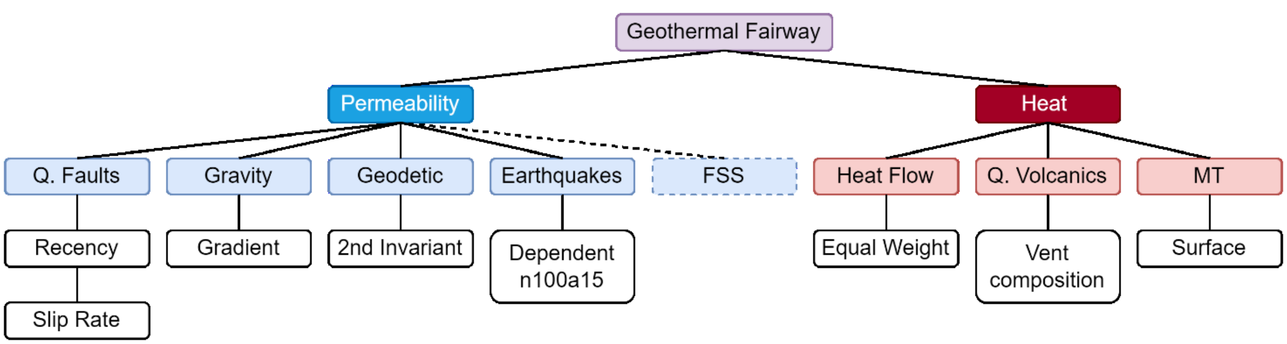

Figure 4: Preliminary play fairway workflow. Blue boxes are parameters for estimating permeability. The dashed box and line for favorable structural settings (FSS) will be added once the FSS database is finalized. Red boxes are parameters for estimating heat. Permeability and heat parameters are combined using logistic regression to produce the regional preliminary geothermal play fairway map.

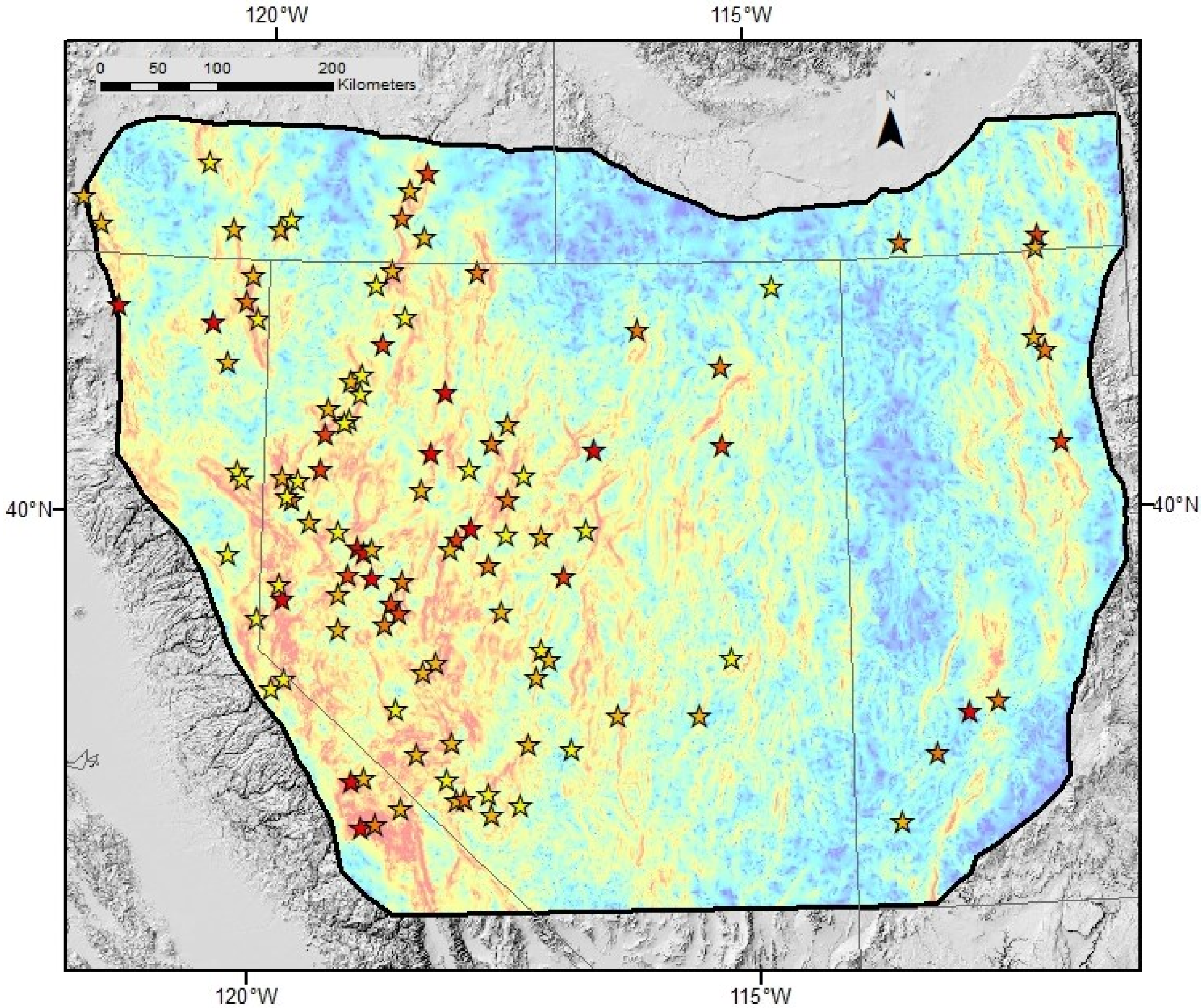

Figure 5: Preliminary regional permeability model. Warmer colors indicate higher favorability and cooler colors indicate lowe r favorability. Colored stars are known geothermal systems (see Figure 2 for key).

4.2 Preliminary Regional Heat Model

Features identified for heat components in the preliminary model included the equal weight heat flow model, the Quaternary volcanic vent super-feature, and the near-surface (2-12 km) and lower crustal (20-50 km) conductance depth slices. The equal weight heat flow model provides an estimate of the conductive heat flow over the study area. The Quaternary volcanic vent super-feature furnishes an estimate of heat related to felsic and mafic Quaternary volcanic activity. The conductance depth slices from MT data were selected as heat parameters because they begin at a depth of 2km, which is generally deeper than most GBR geothermal reservoirs. Therefore, these data may likely provide more insight into potential deep heat sources rather than to convective permeability.

These four layers were analyzed by logistic regression to develop the regional heat model. When these four layers are combined using logistic regression, the lower crustal MT layer shows a negative relationship between conductance values and geothermal favorability, whereas GBR geothermal systems commonly correlate with high conductance values. Therefore, the lower crustal depth slice was removed, and only the remaining three layers were utilized to generate the regional heat model (Figure 4).

The equal weight heat flow model, Quaternary volcanic vent super-feature, and the surface (2-12 km) conductance depth slice were then rerun using logistic regression. The coefficients calculated from this analysis indicate that the relative importance of these layers from greatest to least is 1) near-surface (2-12 km) conductance depth slice, 2) equal weight heat flow model, and 3) the Quaternary volcanic vent super-feature. The coefficients were then utilized to calculate the preliminary heat model (Figure 6). This model generally indicates higher favorability in north-central Nevada and in northeast Nevada to northwest Utah. Regions of lower favorability are generally located in the southern portion of the INGENIOUS study area.

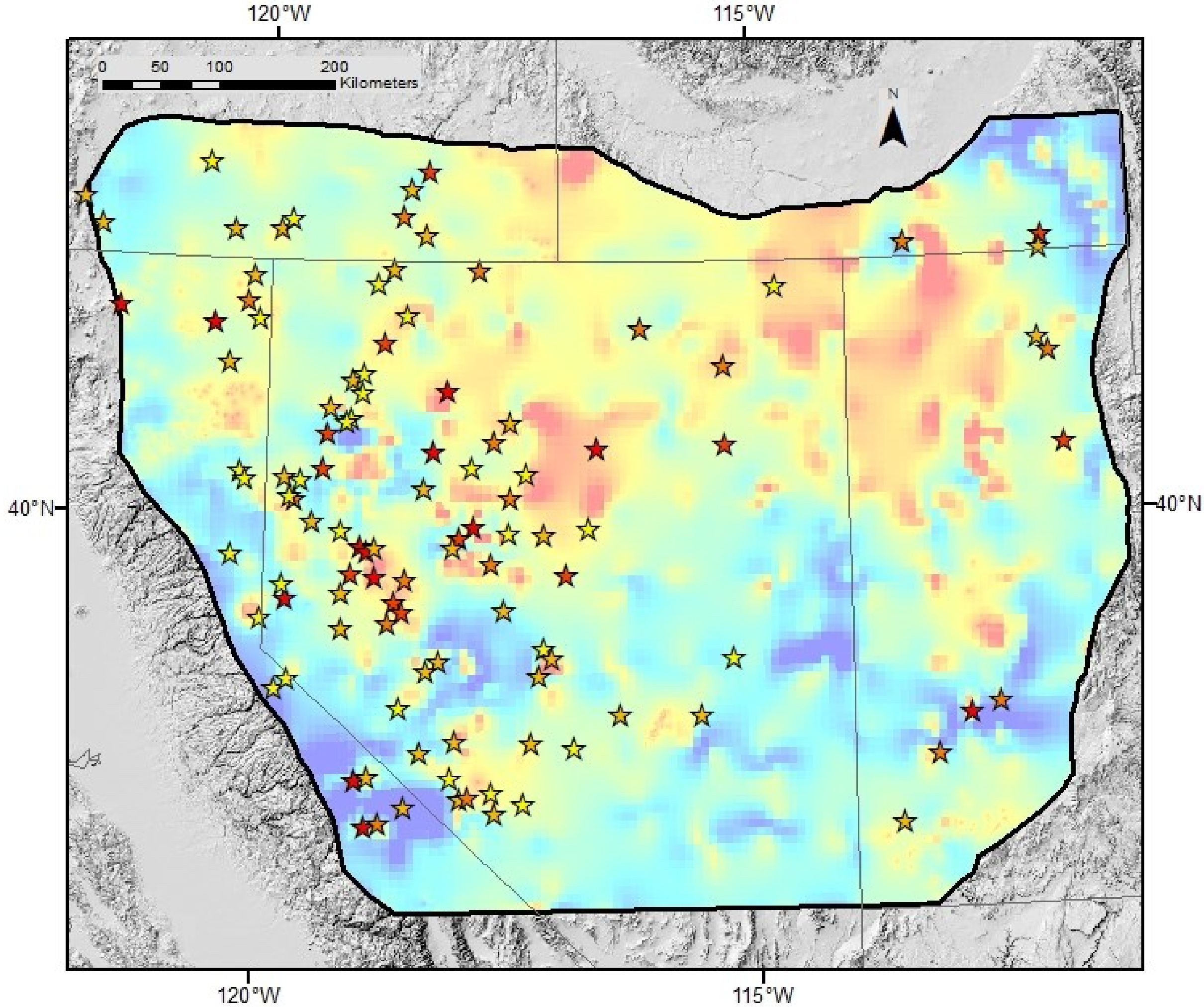

Figure 6: Preliminary regional heat model. Warmer colors indicate higher favorability and cooler colors indicate lower favorability. Colored stars are known geothermal systems (see Figure 2 for key).

4.3 Preliminary Regional Geothermal Fairway Model

The regional permeability and heat models were combined using logistic regression to produce the preliminary geothermal play fairway model (Figure 7). The coefficients from this analysis indicate that permeability is the key contributor, followed by heat. This model generally indicates higher favorability in western Nevada and along the Wasatch Front in Utah. Regions of lower favorability are generally located in eastern Nevada to far western Utah and southwestern Idaho. Overall, there is a good correlation between KGS and areas of high geothermal favorability (Figure 7). Some KGS appear to be disconnected from areas of higher geothermal favorability; however, in some of these cases the individual KGS locations are based on spring data and therefore could be located up to kilometers away from potential subsurface locations of geothermal reservoirs.

5. CONCLUSIONS AND NEXT STEPS

Here, we present the INGENIOUS preliminary regional geothermal PF workflow and fairway maps. INGENIOUS datasets were analyzed with WofE, logistic regression, and other tools to identify statistically significant relationships between data layers and KGS. Additionally, feature engineering has been utilized to extract maximum value from the input data by developing hybrid predictive features consistent with previously identified physiographic relationships for Quaternary faults and Quaternary volcanic vents. The identified key predictive feature layers for permeability include the Quaternary fault super-feature, horizontal gravity gradient, second invariant of strain, and the dependent earthquake rate model ($N = 100$, $\alpha = 0.15$). The identified key predictive feature layers for heat include the equal weight heat flow model, the Quaternary volcanic vent super-feature, and the near-surface (2-12 km) conductance depth slice. These heat and permeability models were statistically integrated using logistic regression within the constraints of a PFA architecture to produce a preliminary GBR geothermal fairway model. This initial play fairway workflow was utilized to develop new preliminary predictive GBR geothermal fairway maps, which improve our understanding of GBR geothermal resources and can facilitate identification of potential hidden systems. These preliminary models and maps are an improvement on previously published maps and workflows, as they balance the input of data-driven statistics and valuable expert-knowledge, as well as incorporating additional data sets and higher resolution data over the broad INGENIOUS study area.

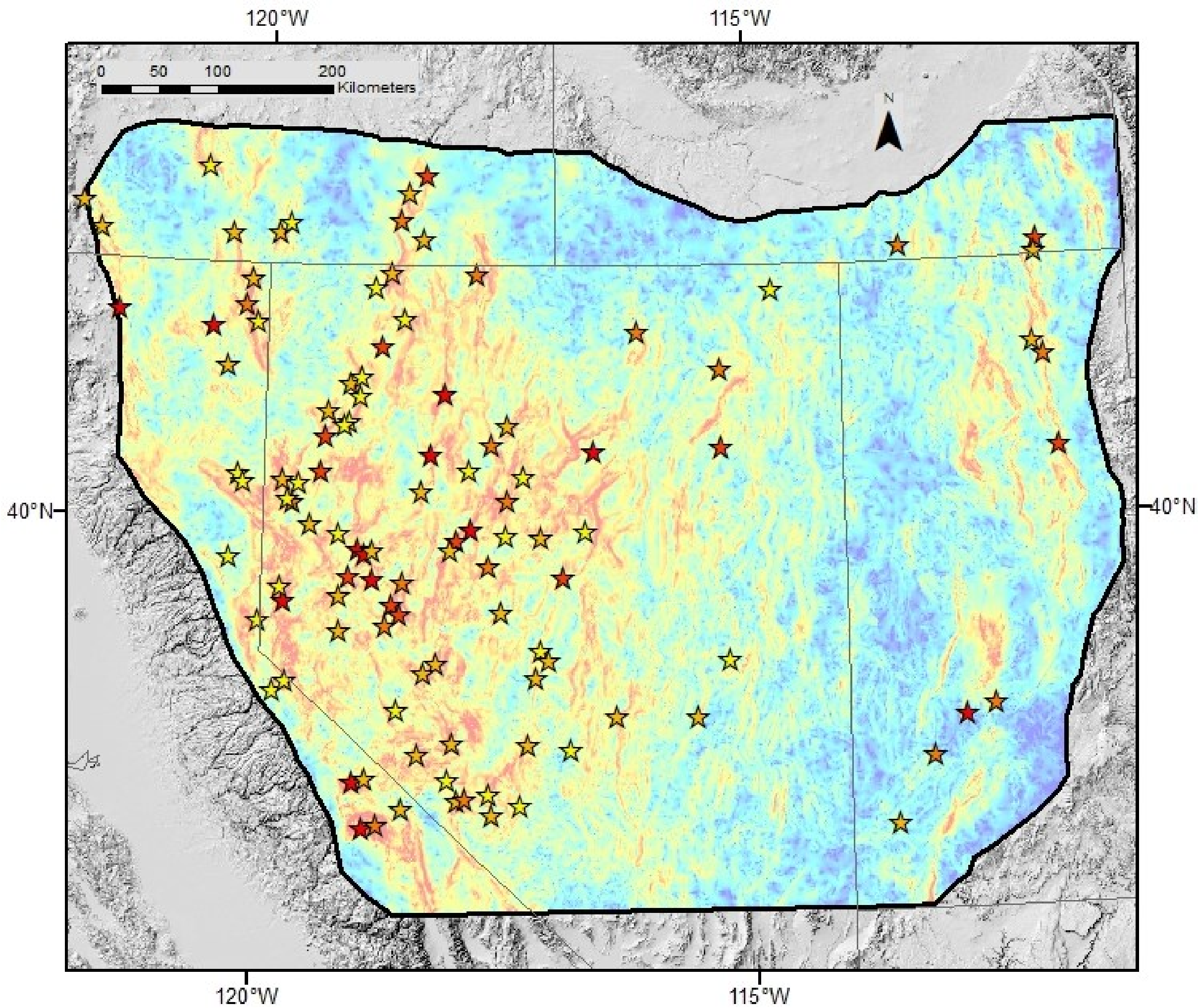

Figure 7: Preliminary regional geothermal fairway model. Warmer colors indicate higher favorability and cooler colors indicate lower favorability. Colored stars are known geothermal systems (see Figure 2 for key).

We have also identified several next steps, as we move toward developing the finalized INGENIOUS PF workflow and geothermal favorability maps. One of these key steps is integrating the favorable structural settings database (e.g., Faulds and Hinz, 2015; Faulds et al., 2021a,b) into this analysis once that database is finalized. Additionally, we plan to evaluate the inclusion of Quaternary volcanic vent ages into the Quaternary volcanic vent super-feature. Other geophysical features that will be assessed in further detail include the magnetic data and a depth-to-basement layer derived from gravity data. Paleo-geothermal deposits, well and spring data, and two-meter temperature data were not included in the geothermal fairway workflow and map. It is anticipated that these datasets may be utilized in future iterations as degree-of-exploration or direct evidence layers that would serve as higher-level add-on products to augment the PF workflow steps after generating the initial geothermal fairway map. We are also evaluating the fluid geochemistry data, heat flow residuals, well and spring data, and paleo-geothermal deposits for the potential of including some of those data points as additional positive and negative training sites.

6. ACKNOWLEDGMENTS

This project is funded by U.S. Department of Energy - Geothermal Technologies Office under award DE-EE0009254 to the University of Nevada, Reno. Thank you to the entire INGENIOUS team (Great Basin Center for Geothermal Energy, Nevada Bureau of Mines and Geology, University of Nevada Reno, Aprovechar Lab L3C, Cyrq Energy, Inc., Geothermal Resource Group, Hi-Q Geophysical, Inc., Idaho Geological Survey, Innovate Geothermal Ltd, Lawrence Berkeley National Laboratory, National Renewable Energy Laboratory, Teverra LLC (formerly Petrolern Ltd.), U.S. Geological Survey, and the Utah Geological Survey) for their contributions to the INGENIOUS project which supported this work. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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