Exploring Geothermal Potential of Great Basin Sub-Regions

Preprint

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Exploring Geothermal Potential of Great Basin Sub-Regions

Nicole R. Hart-Wagoner[1], Cary Lindsey[1], Whitney Trainor-Guitton[2], Mark Coolbaugh[1], and James E. Faulds[1]

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Keywords

INGENIOUS, Great Basin, sub-region, geothermal, exploration, statistics, PCA, k-means

ABSTRACT

The INnovative Geothermal Exploration through Novel Investigations Of Undiscovered Systems (INGENIOUS) project aims to discover new, economically viable hidden geothermal systems in the Great Basin region by building on previous work in play fairway analysis and machine learning. A key objective of this project is to develop an exploration workflow to reduce geothermal exploration risks for hidden geothermal systems. A single preliminary play fairway workflow was developed from the assessment of the regional INGENIOUS geological, geophysical, and geochemical datasets. This workflow provided new preliminary predictive geothermal fairway maps for the INGENIOUS study area, which encompasses most of Nevada, western Utah, southern Idaho, southeastern Oregon, and easternmost California. However, a recent study (incorporating machine learning techniques) of a portion of Nevada identified four geologic domains and determined that the relative importance of individual datasets or features as indicators of geothermal potential may differ across these domains. The INGENIOUS study area includes a much larger and more geologically diverse region; therefore, additional geologic domains or sub-regions are expected. To assess the sub-regions in the INGENIOUS study area, principal component analysis and k-means clustering were applied. Preliminary results indicate that the INGENIOUS regional data cluster into groups that relate to different geologic domains in the Great Basin region. These include domains such as the Walker Lane, extensional western Great Basin region, broad lower strain region in the eastern Great Basin of western Utah and eastern Nevada, Quaternary volcanic fields, and the area adjacent to the Snake River Plain. These clusters are assessed to determine the key geologic drivers of the identified clusters. Understanding this variability can provide key insights for the exploration and characterization of hidden geothermal systems in the Great Basin region and could indicate the need to develop multiple geothermal conceptual models and play fairway workflows for the INGENIOUS study area.

1. Introduction

The Great Basin region in the western United States (Figure 1) 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 geothermal potential could be much higher (e.g., Williams et al., 2009). Many of the historical discoveries of conventional hydrothermal systems in the Great Basin region have surface thermal features. However, future geothermal potential is thought to lie mostly in hidden or blind geothermal systems that lack surface thermal features such as hot springs (e.g., Coolbaugh et al., 2007; Faulds et al., 2019). In recent years, there has been an extensive effort to identify and develop more hidden geothermal systems (e.g., Faulds and Hinz, 2015; Faulds et al., 2021 a,b,c; Craig et al., 2021). The INnovative Geothermal Exploration through Novel Investigations Of Undiscovered Systems (INGENIOUS) project aims to discover new, economically viable hidden geothermal systems in the Great Basin region by integrating new and established techniques to develop a play fairway workflow that can reduce exploration risk. The study area for the project includes most of Nevada, western Utah, southern Idaho, southeastern Oregon, and easternmost California (Figure 1). A single preliminary play fairway workflow was developed from the assessment of the regional INGENIOUS geological, geophysical, and geochemical datasets, which provided new preliminary predictive geothermal fairway maps for the INGENIOUS study area (Hart-Wagoner et al., 2024). While the preliminary play fairway workflow is a crucial first step in producing updated predictive geothermal fairway maps, additional refinements are being evaluated to enhance that workflow.

One refinement being evaluated is the use of sub-regions in the regional play fairway workflow. This approach stems from the findings of Smith et al. (2023), who applied PCAk to the Nevada PFA study area in northern Nevada. They identified four geologic domains including the Walker Lane, western Great Basin, central Nevada seismic belt, and the carbonate aquifer. PCAk was applied to the Nevada PFA study area to determine the relative importance of individual features, as indicators of geothermal potential may differ across the region in the different geologic domains. The INGENIOUS study area includes a much larger and more geologically diverse region; therefore, additional geologic domains or sub-regions are expected. The existence of these geologically distinct sub-regions could indicate the need to develop multiple conceptual models and play fairway workflows for the INGENIOUS study area. Principal component analysis and k-means clustering were applied to the identified known geothermal systems within the INGENIOUS study area. Subsequently, the clusters were analyzed to determine how they might relate to geologically distinct sub-regions of the Great Basin region. We then weigh the key contributing features for known geothermal system clusters, providing insight into 1) the viability of the single preliminary play fairway workflow (Hart-Wagoner et al., 2024) and 2) the need for different geothermal conceptual models and exploration workflows for sub-regions of the INGENIOUS study area in the Great Basin region.

2. Data and Methods

2.1 Data

In Phase I of the INGENIOUS project, a regional-scale geoscience compilation of 14 datasets was completed for the 494,269 km² study area. These included: 1) location of Quaternary faults, 2) slip rates on Quaternary faults, 3) age or recency of faulting, 4) slip-dilation tendency (TSTD) on Quaternary faults, 5) active and paleo-geothermal features, 6) Quaternary volcanic distribution, 7)

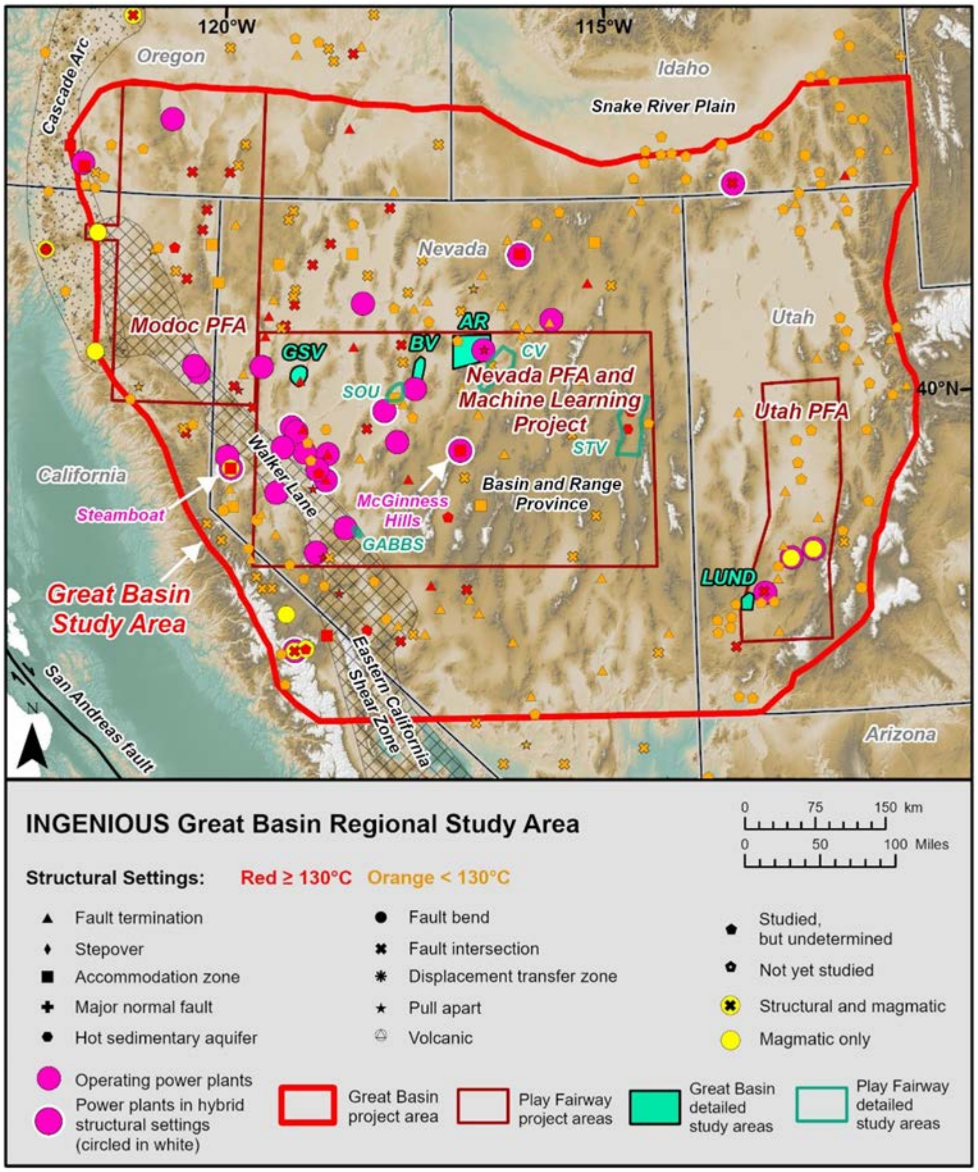


Figure 1: Regional setting of Great Basin study area for the INGENIOUS project, with locations of known geothermal systems, identified structural settings, previous PF projects (Modoc, Nevada, and Utah), and current detailed study areas (Granite Springs Valley-GSV; Argenta Rise-AR, Buffalo Valley-BV,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

gravity data and models, 8) magnetic data and models, 9) magnetotelluric (MT) data and models, 10) geodetic strain rate, 11) earthquake distribution, 12) regional heat flow/temperatures, 13) temperature-geochemical data from wells and springs, and 14) two-meter temperature data. These datasets are a mixture of categorical and continuous numerical data. Many of the continuous numerical datasets were utilized in this study in their original form. However, categorical data needed to be transformed to continuous numerical datasets through feature engineering. An example was combining the fault and fault attribute data to generate Quaternary fault models for recency and slip rate (Hart-Wagoner et al., 2023). In this case, Euclidean distance and Euclidean allocation were utilized to transform these datasets into continuous grids. Then, weights-of-evidence (WofE) analysis was used to identify statistical relationships between known geothermal systems and the data to build new Quaternary fault attribute models that were continuous gridded surfaces (Hart-Wagoner et al., 2023).

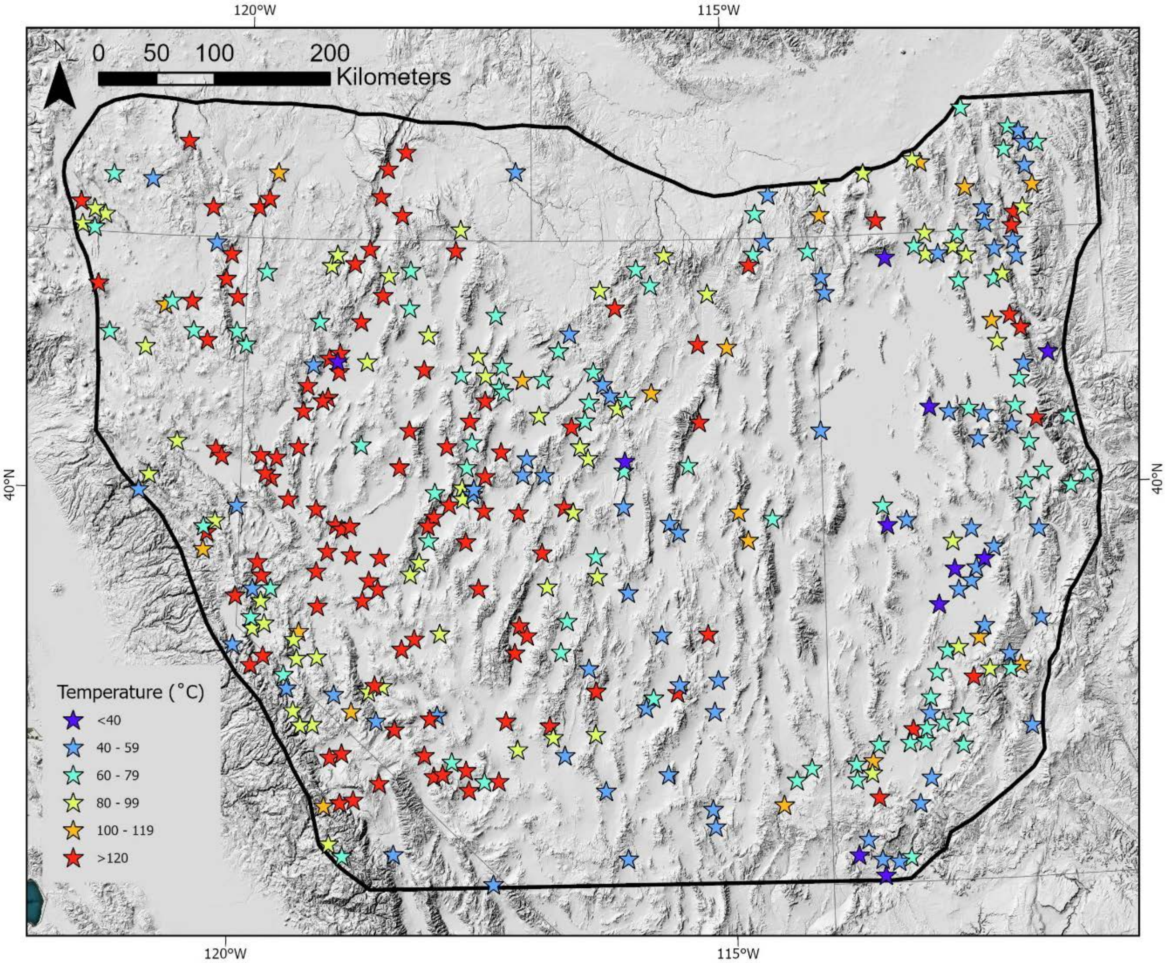


Figure 2: Compiled known geothermal systems in the INGENIOUS study area >37°C. Data from the INGENIOUS datasets were extrapolated at each of these sites.

The data utilized in this study included features for earthquake rate density (Ayling et al., 2022), electrical conductance depth slices estimated from modeling of MT data (Peacock and Bedrosian, 2022), conductive heat flow (DeAngelo et al., 2022), depth to basement and potential field geophysical data (Glen et al., 2022), geodetic data (Ayling et al., 2022), Quaternary faults and fault attributes (Hart-Wagoner et al., 2023), and Quaternary volcanic vent composition. From these datasets, a total of 22 features were assessed in this analysis. The earthquake features included one independent (i.e., main shock) and one dependent earthquakes (i.e., aftershocks, foreshocks, and swarms) rate density model using N = 100 and an α value of 0.15 (N is the nearest number of earthquakes that were considered in generating the earthquake rate density map and α is a "declustering parameter" that distinguishes between independent and dependent earthquake events). The MT features included depth slices for: near-surface (2-12 km), middle crust (12-20 km), lower crust (20-50 km), upper mantle (50-90 km) and mantle (90-200 km). The potential field geophysical derived features included isostatic residual gravity anomalies, horizontal gravity gradient, magnetic intensity, horizontal magnetic gradient, and depth to basement. The geodetic features included the second invariant, the dilatation rate, and the shear rate. The Quaternary fault features included recency, slip rate, and TSTD models. Lastly, the Quaternary volcanic features included distance to felsic, intermediate, and mafic volcanic vents.

A total of 354 known geothermal systems with known or estimated temperatures >37˚C in the INGENIOUS study area were identified as training sites for this analysis (Figure 2). These systems are either producing geothermal systems (i.e., contain operating geothermal power plants), identified geothermal systems that have not yet been developed, or geothermal systems that have been identified from measured well temperatures or temperatures estimated using geothermometry. A data value from each of the features listed above was extracted at each of the 354 known geothermal systems. These data were then utilized for PCAk modeling.

2.2 Unsupervised PCAk Modeling

Principal component analysis (PCA) (e.g., Pearson, 1901; Hotelling, 1933; Jolliffe, 2002) and k-means clustering (e.g., MacQueen, 1967; Lloyd, 1982; Jain, 2010) are unsupervised machine learning techniques that have been utilized for exploratory data analysis to support dimensionality reduction and to group and visualize multidimensional data. These methods have previously been used in tandem (PCAk) and shown utility in developing geothermal potential maps and guiding geothermal exploration studies at a finer regional scale (e.g., Smith et al., 2023). A similar approach is applied here to a different set of features to evaluate variability in the identified known geothermal systems of the much larger INGENIOUS study area.

PCA is a dimensionality reduction method that rotates and transforms the data to identify the principal components that account for the most variance in the input data. Since we are considering many potential features to characterize INGENIOUS known geothermal systems, PCA can be utilized to balance the consideration of these features, while maximizing the amount of explained variance considered in the analysis in fewer dimensions. The principal components are ordered by the proportion of the variance that they account for in the dataset, with lower principal component numbers accounting for more variance. A plot of the explained variance ratio can therefore be utilized to determine the number of principal components that should be considered in the analysis. These principal components also have loading values that indicate the contribution of each original feature to the principal components (e.g., Smith et al., 2023). These values can be used to identify which features are most influential in explaining the variance captured by each principal component.

K-means clustering is a method to group and visualize data for a user-defined number of clusters (k). The number of clusters can be defined by testing various number of clusters and calculating the within-cluster sum of squares for each tested k value. As the number of clusters increases, the within-cluster sum of squares generally decreases. The optimal number of clusters is usually determined where the within-cluster sum of squares difference becomes marginal. Once the optimal number of clusters is determined, K-means can build on the identified principal components by identifying data clusters and optimal centroid locations from the identified principal components. These clusters can then be mapped to illustrate the spatial extent of known geothermal system clusters. The loading values from the PCA analysis can be utilized to assess the importance of the features in each cluster (e.g., Smith et al., 2023). The ranking of features in each cluster can be used to evaluate the variability of known geothermal systems between different clusters.

3. Results

3.1 PCA Results

The PCA results indicate that none of the identified principal components explains more than 23.6% of the total variance of the dataset (Figure 3A). Four principal components are required in order to explain ~50% of the variance, while 10 components are required to explain 80% of the variance, and 14 components are required to explain ~90% of the variance (Figure 3B). To reduce dimensionality while still maximizing the amount of variance utilized in k-means, 14 principal components were retained and utilized in k-means clustering.

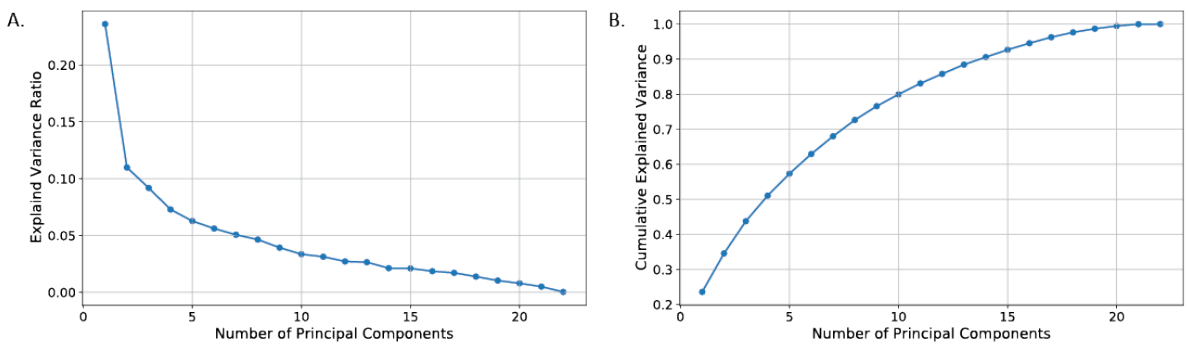


Figure 3: PCA scree plots. A. Explained variance ratio for each individual principal component. B. Cumulative explained variance ratio for combined principal components.

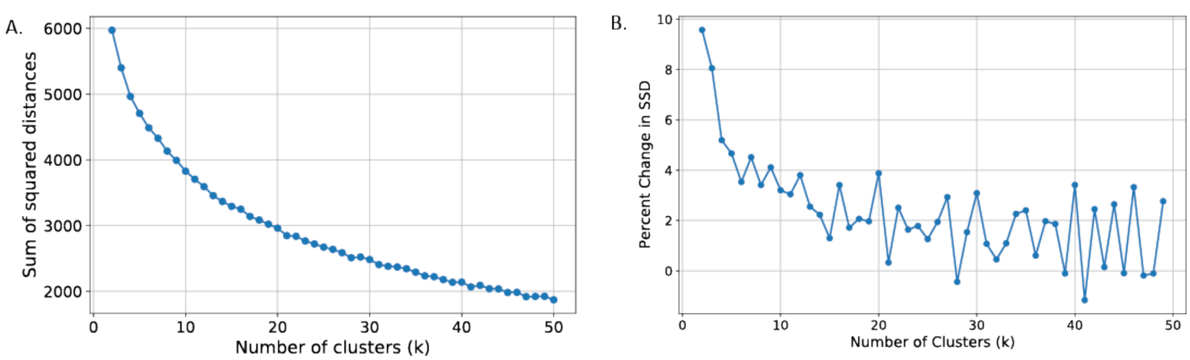


Figure 4: K-means scree plots. A. Within-cluster sum of squares for different k values. B. Percent change in the within-cluster sum of squares between different k values.

3.2 K-means Results

K-means clustering was completed using the PCA-transformed data (14 principal components). To identify the optimal number of clusters, k values from two to 50 were tested. The within-cluster sum of squares (Figure 4A) and the percent change of within-cluster sum of squares (Figure 4B) were utilized to identify six clusters for these data. If more than six clusters were utilized, there was only a marginal decrease in the within-cluster sum of squares.

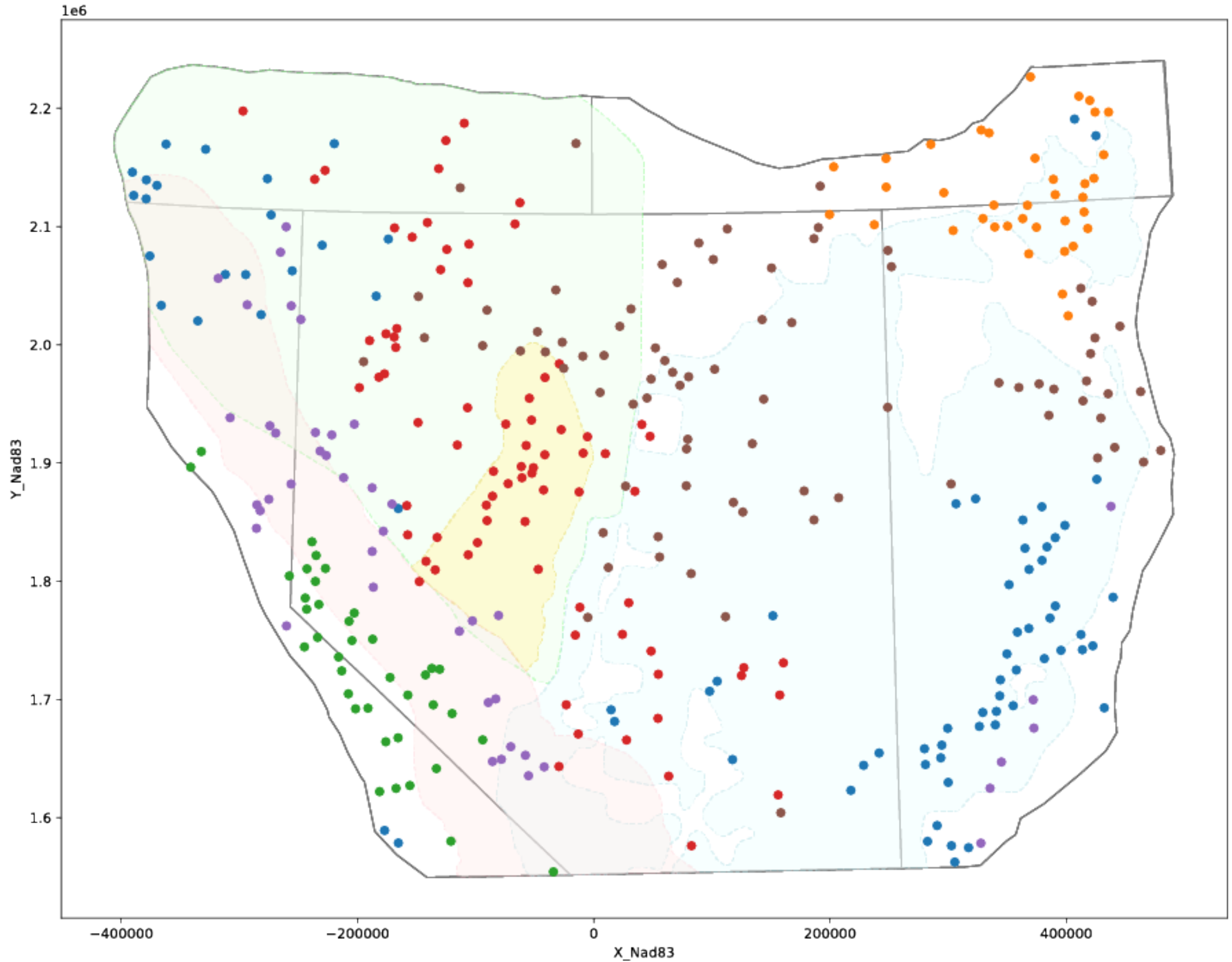


Figure 5: PCAk cluster map for the resulting six clusters. Different clusters of known geothermal systems are represented by different colored points. Polygons are based on the geologic domains utilized by Smith et al. (2023) and illustrate potential geologic sub-regions: green polygon – western Great Basin, red polygon – Walker Lane, yellow polygon – central Nevada seismic belt, blue polygon – carbonate aquifer.

The six clusters were then mapped to illustrate the geographic extent of the clusters (Figure 5). The sum of loading values from PCA were utilized to assess feature importance within each cluster (Figure 6). The features in each cluster were ordered based on the sum of loading scores to illustrate the relative contribution of features to the cluster (Figures 7-9). A high positive loading value indicates a strong contribution to the cluster and a positive relationship between the high feature values and high PC scores. A high negative loading value also indicates a strong contribution to the cluster and a negative relationship between high feature values and high PC scores.

The green cluster has 38 known geothermal systems, which are generally clustered in the southwest margin of the study area along the southwestern edge of the Walker Lane (Figure 5). Within the green cluster, the sum of loading values for this cluster has the strongest positive and negative relationships (Figure 6). The strongest contributing features with positive relationships are geodetic data, earthquake rate density, and Quaternary faults, and the strongest contributing features with negative relationships are isostatic gravity and distance to Quaternary volcanic vents (Figure 7A). These results indicate that the known geothermal systems in this cluster have an

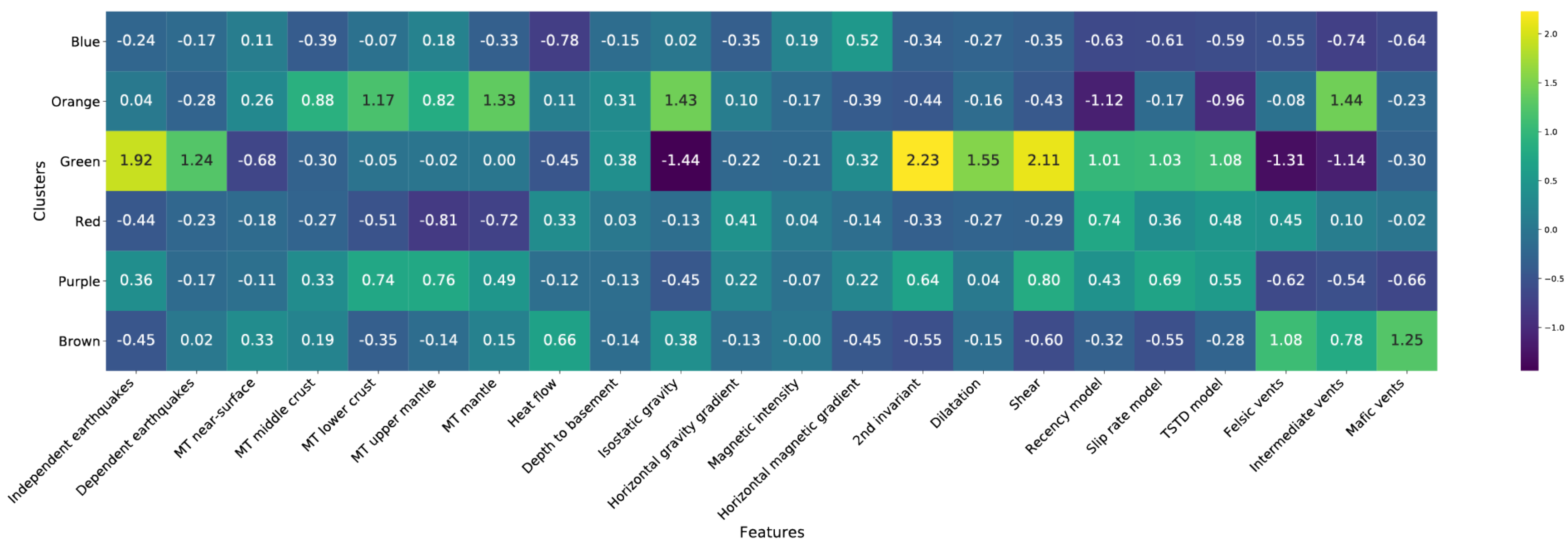


Figure 6: PCAk feature matrix for feature influence in each cluster. The value in the box is the sum of the loading values which is either negative or positive. Warmer colors indicate a positive relationship, and cooler colors indicate a negative relationship.

association with high second invariant and shear rates, high earthquake rate density, low isostatic gravity values, long distances to Quaternary volcanic vents, and high TSTD and slip rate.

The purple cluster has 43 known geothermal systems and is generally clustered along the southwest margin of the study area but more interior than the green cluster along the northeastern edge of the Walker Lane (Figure 5). Compared to some of the other clusters, the sum of loading values for this cluster are all relatively low (Figure 6). The strongest contributing features with positive relationships are geodetic data, MT, and Quaternary faults, and the strongest contributing factors with negative relationships are distance to volcanic vents (Figure 7B). These results indicate that the known geothermal systems in this cluster have an association with high shear rates, high conductance in the upper mantle and lower crust, high slip rates, and short distances to Quaternary volcanic vents.

The red cluster has 79 known geothermal systems and is generally more dispersed in the western part of the Great Basin study area (Figure 5). Compared to some of the other clusters, the sum of loading values for this cluster are all relatively low (Figure 6). The strongest contributing features with negative relationships are MT and earthquake rate density, and the strongest contributing features with positive relationships are Quaternary faults and distance to felsic volcanic vents (Figure 8A). These results indicate that the known geothermal systems in this cluster have an association with low conductance in the lower crust, upper mantle, and mantle, low earthquake rate density, long distances to Quaternary volcanic vents, and high TSTD.

The brown cluster has 80 known geothermal systems and is a bit more dispersed in the eastern part of the Great Basin study area (Figure 5). Compared to the other clusters, the sum of loading values for this cluster are higher with strong positive relationships (Figure 6). The strongest contributing features with positive relationships are distance to volcanic vents and heat flow, and the strongest contributing features with negative relationships are geodetic data and slip rate of Quaternary faults (Figure 8B). These results indicate that the known geothermal systems in this cluster have an association with long distances to Quaternary volcanic vents, high conductive heat flow, low second invariant and shear rates, and low slip rates.

The orange cluster has 37 known geothermal systems and is generally clustered in the northeast corner of the study area, adjacent to the Snake River Plain (Figure 5). Relative to some clusters, the sum of loading values for this cluster are higher with strong positive relationships (Figure 6). The strongest contributing features with positive relationships are distance to intermediate volcanic vents, isostatic gravity, MT, and a negative relationship with Quaternary fault recency and TSTD (Figure 9A). These results indicate that the known geothermal systems in this cluster have an association with long distances to Quaternary intermediate volcanic vents, high isostatic gravity values, high conductance in the mantle and lower crust, low TSTD, and older recency.

The blue cluster has 77 known geothermal systems and is generally clustered in the northwest corner of the study area near the Modoc Plateau and along the southern edge of the Wasatch Front (Figure 5). Compared to some of the other clusters, the sum of loading values for this cluster are all relatively low and exhibit stronger negative relationships (Figure 6). The strongest contributing features with negative relationships are heat flow, distance to volcanic vents, and Quaternary fault attributes (Figure 9B). These results indicate that the known geothermal systems in this cluster have an association with low conductive heat flow values, short distances to Quaternary volcanic vents, older recency, low slip rate, and low TSTD.

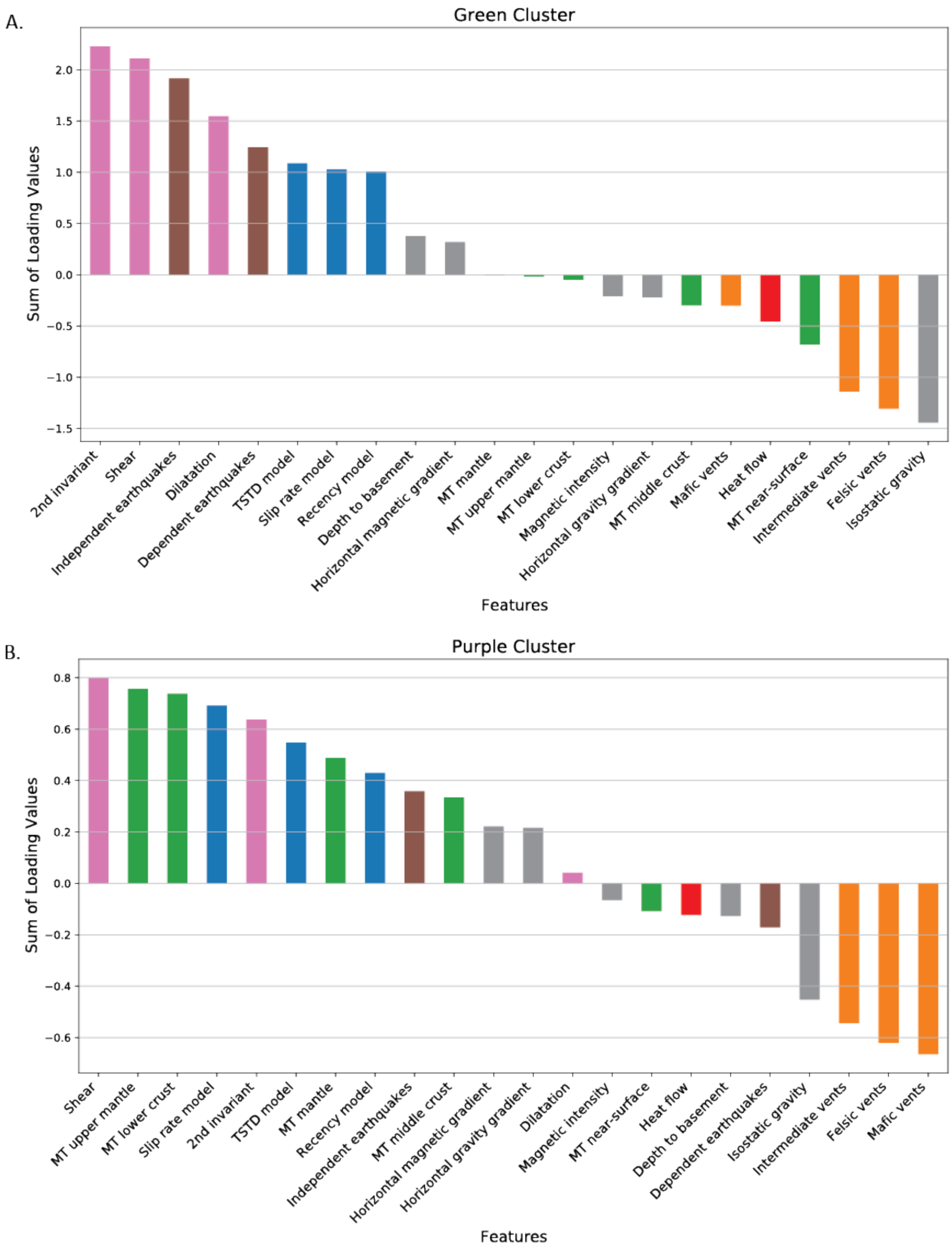
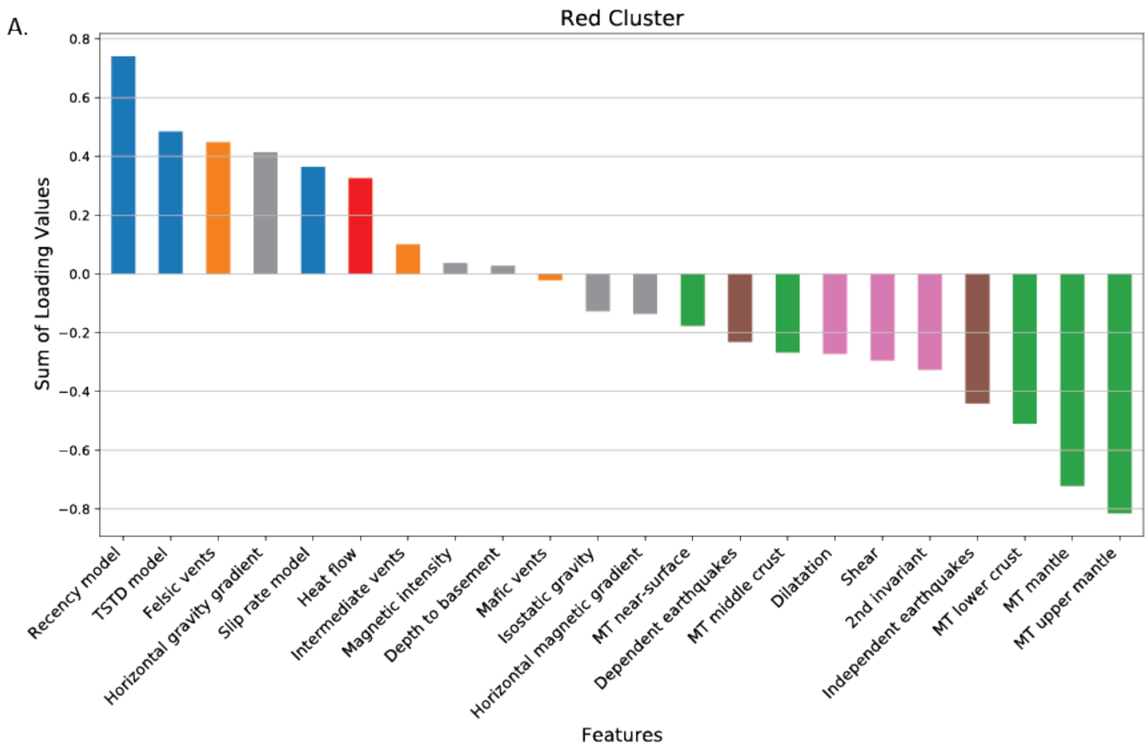


Figure 7: Relative sum of loading values ranking from high to low for the green (southwest Walker Lane) cluster (A) and Purple (northeast Walker Lane) cluster (B). Bars are colored for like data types; pink: geodetic, red: heat flow, orange: Quaternary volcanic vents, green: MT, blue: Quaternary fault attributes, brown: earthquake rate density, gray: potential field.



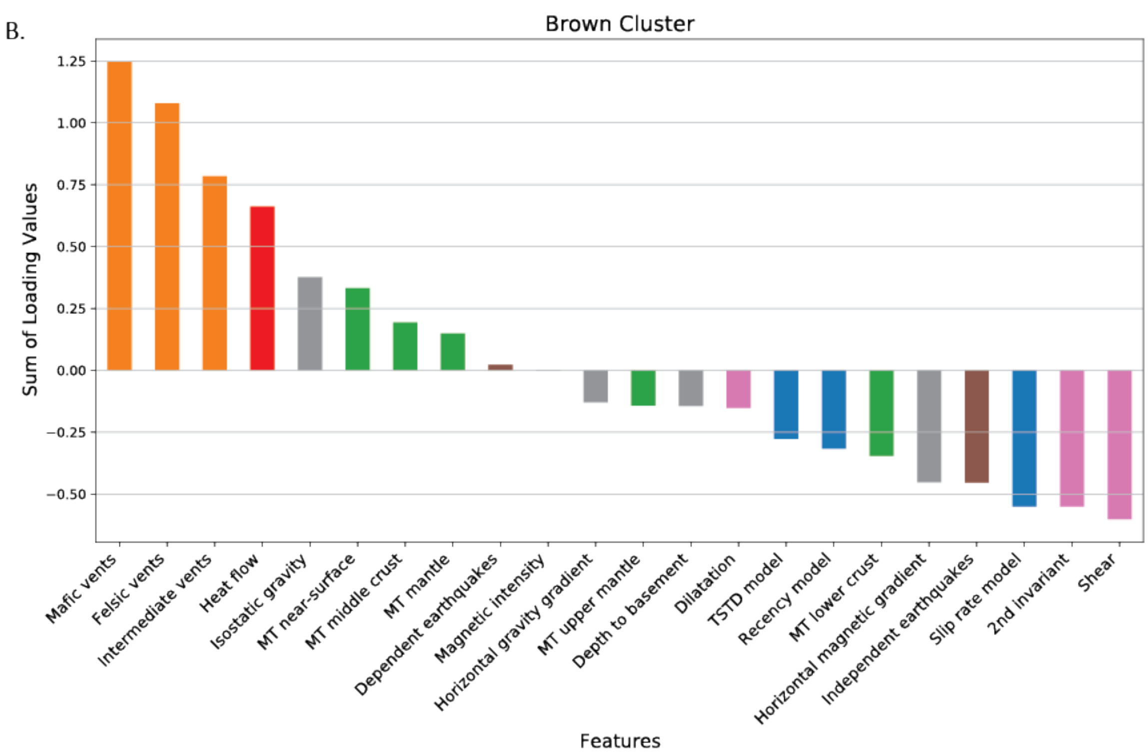
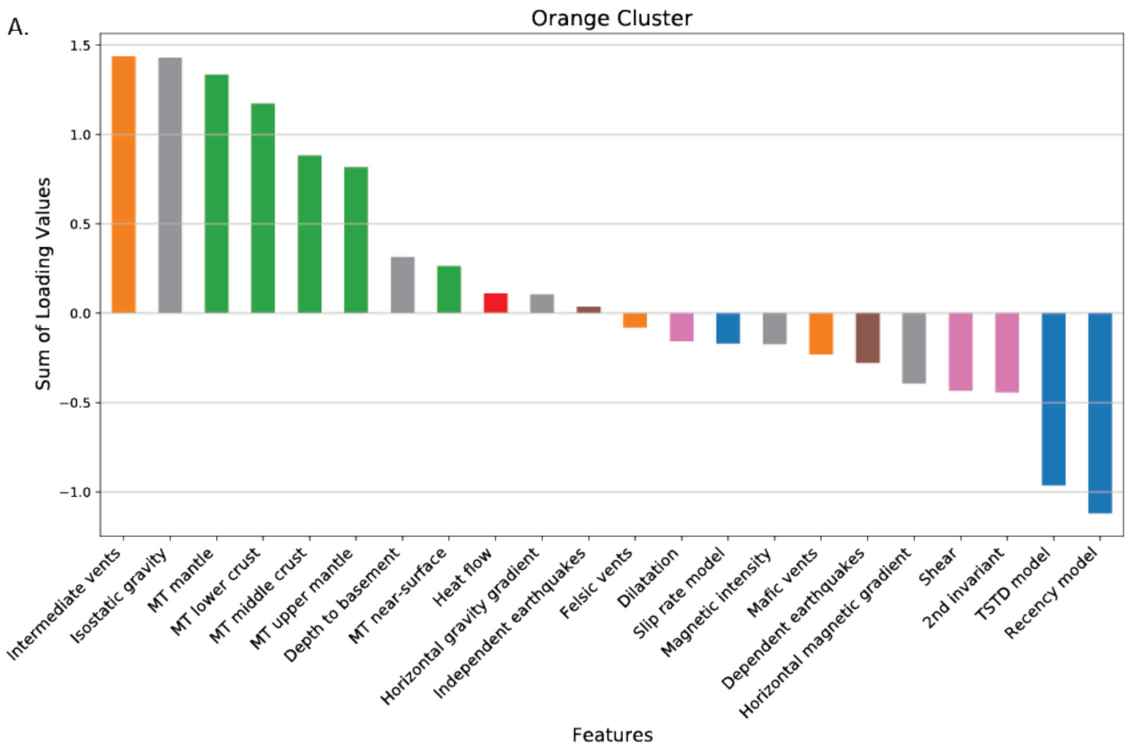


Figure 8: Relative sum of loading values ranking from high to low for the red (western Great Basin) cluster (A) and the brown (eastern Great Basin) cluster (B). Bars are colored for like data types; pink: geodetic, red: heat flow, orange: Quaternary volcanic vents, green: MT, blue: Quaternary fault attributes, brown: earthquake rate density, gray: potential field.



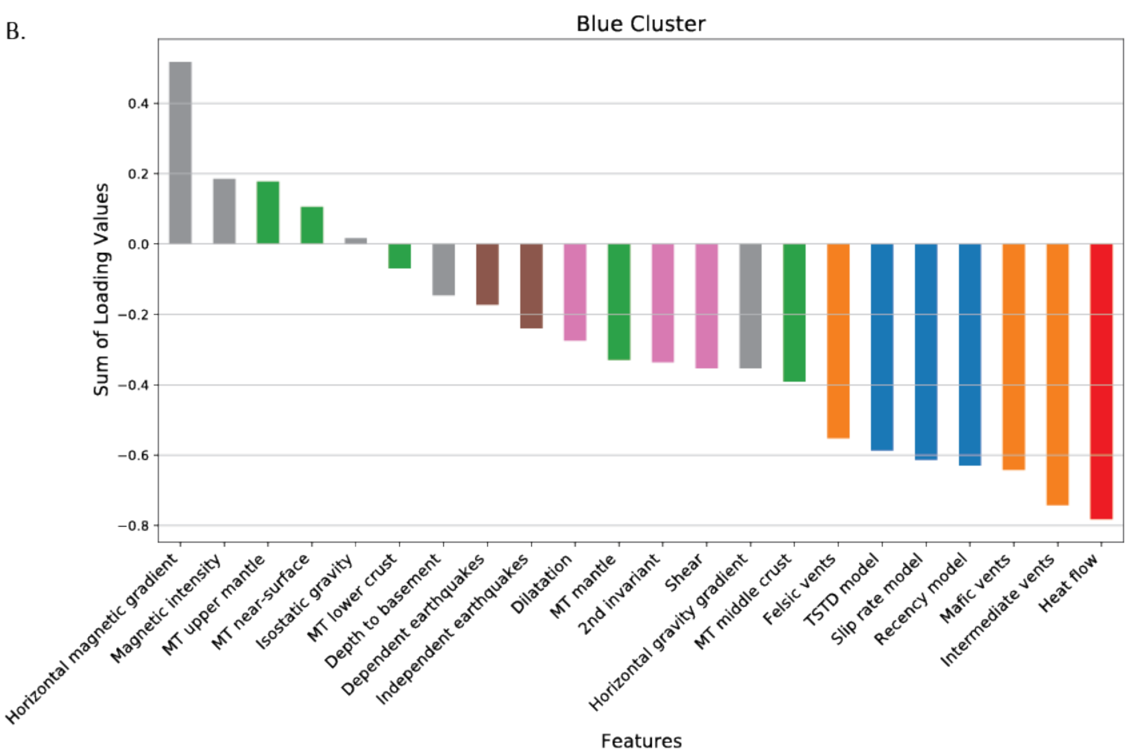


Figure 9: Relative sum of loading values ranking from high to low for the orange (adjacent to the Snake River Plain) cluster (A) and the blue (Quaternary volcanic field) cluster (B). Bars are colored for like data types; pink: geodetic, red: heat flow, orange: Quaternary volcanic vents, green: MT, blue: Quaternary fault attributes, brown: earthquake rate density, gray: potential field.

4. Discussion

4.1 PCA and K-means

These preliminary results indicate that while dimensionality reduction can be utilized, there are still many principal components required to explain the variance in the datasets. This was consistent in all the tests using different numbers of input features. The number of retained principal components utilized for k-means was also tested. If the number of principal components varied, the resulting clusters did not change significantly. The resulting clusters were still grouped in geographic areas that can be related to different geologic domains, independent of using geographic location data or assigning known geothermal systems to different geologic domains. As the number of principal components varied, the most variation in cluster designation occurred along the Wasatch Front. The geographic distribution of clusters in the western Great Basin remained largely consistent across the various tested numbers of principal components.

4.2 Clusters

Due to the western Great Basin clusters remaining largely consistent, this indicates high confidence in the differentiation of the clusters in the western Great Basin region. This includes the distinction of the green cluster on the southwestern side of the Walker Lane and the purple cluster on the northeastern side of the Walker Lane. The differentiation of these clusters seems to be mostly driven by geodetic data with higher strain rates in the green cluster and still high, but slightly lower strain rates in the purple cluster. Another difference noted in these clusters is that the green cluster is associated with slightly higher slip rates and slightly longer distances to some Quaternary faults than the purple cluster. This could be another line of evidence to support that geothermal systems in the green cluster may be associated with slightly longer distances to Quaternary faults potentially due to the high slip rates that commonly correspond to strike-slip faults or to very long and linear normal faults that are not as favorable for geothermal activity except in transtensional pull-apart basins or displacement transfer zones (Faulds et al., 2010, 2021b,c). These long linear normal faults may lack structural complexity and discontinuities, which could limit geothermal favorability, or these faults with high slip rates may generate more clay gouge that limits the permeability of the fault and lowers geothermal favorability (Faulds et al., 2010, 2021a,b,c; Hart-Wagoner et al., 2023). Either way, the variability between these clusters could be utilized to better characterize the geothermal systems along the Walker Lane.

These results also help to distinguish between the more dispersed clusters in the western and eastern Great Basin. The main distinguishing factor for these two clusters seems to be Quaternary fault attribute data. The brown cluster of the eastern Great Basin appears to have lower slip rates and older Quaternary faulting. This cluster also has longer distances to Quaternary faults and paleo-geothermal deposits, which could indicate that there is some difference in how the geothermal systems in the brown and red clusters interact with the near sub-surface to surface. It has previously been suggested that geothermal systems in the eastern Great Basin could be concealed within the carbonate aquifer domain (e.g., Smith et al., 2023). The longer distances to Quaternary faults and paleo-geothermal deposits identified in this study may support that hypothesis, as concealment could cause geothermal fluids to travel greater distances through the subsurface before reaching the surface. From the analysis of the features utilized in this study, it is not clear what feature could be causing potential concealment of geothermal systems in the eastern Great Basin. Additional features, such as lithological data (Smith et al., 2023) may provide more insight into the factors that could be causing concealment in this sub-region.

The orange cluster that is adjacent to the Snake River Plain has strong positive contributing features of MT depth slices (middle crust to mantle) and isostatic gravity. This indicates that in this sub-region, there may be a conductive and dense body in the sub-surface. More work is needed to identify how this is impacting geothermal systems in this sub-region. This cluster also has strong negative contributing factors indicating that these systems have a relationship with low TSTD and older recency. This may indicate that these older Quaternary faults may not be oriented optimally to slip or dilate. This may suggest that Quaternary faulting is not as significant of a positive factor for geothermal systems in this sub-region.

The blue cluster is the only cluster that includes two geographic areas of the study area. While this cluster has weaker contributing factors than most of the other clusters, the key contributing feature for this cluster is distance to Quaternary volcanic vents, and this cluster aligns with the major Quaternary volcanic fields of the Great Basin. While Quaternary volcanic fields and this cluster do not compose a large portion of the Great Basin, they are still an important distinction because they offer insight into how the relationships between features and geothermal systems in these volcanic regions vary from other sub-regions of the Great Basin. Generally, these results show inverse relationships with many of the features that are key contributing features in much of the rest of the Great Basin, such as geodetic data, earthquake rate density, and Quaternary fault attributes. The distinctions that this cluster provides are key to more accurately model geothermal favorability in the volcanic fields of the INGENIOUS study area.

4.3 Distribution of Known Geothermal Systems between Clusters

The number of known geothermal systems in each cluster ranges from 37-80, with the highest number of geothermal systems occurring in the brown (n=80), red (n=79), and blue (n=77) clusters and nearly half as many geothermal systems in the orange, green, and purple clusters. This indicates that there are more identified geothermal systems in the eastern Great Basin, western Great Basin, and Quaternary volcanic field domains. However, this count considers both lower and higher temperature geothermal systems. If only the higher temperature systems are considered, the distribution of geothermal systems from highest to lowest is: red (n=42), purple (n=23), brown (n=15), green (n=13), blue (n=13), and orange (n=3). This could imply that the potential for higher temperature geothermal systems is greater in the western Great Basin and along the Walker Lane. Alternately, this could also suggest that current geothermal exploration has not found the key to identifying higher temperature geothermal systems in the other sub-regions.

The estimated temperatures of the higher temperature systems in each cluster were also assessed (Figure 10). This shows that the blue cluster (Quaternary volcanic fields) contains the highest temperature systems but also has the largest range in temperature. The mean temperature for this cluster is 175 ˚C. While the orange cluster (adjacent to the Snake River Plain) only has a few higher-temperature known geothermal systems, these have the smallest temperature range and a mean temperature of 172˚C. This could suggest that while there are few identified systems in this sub-region, there may be high potential for additional higher temperature systems, if we can isolate the best exploration approach for identifying hidden systems in this sub-region. Similarly, the brown cluster (eastern Great Basin) has a mean temperature of 170˚C, indicating there may be high potential to identify additional higher temperature systems in the eastern Great Basin as well.

The mean temperatures for geothermal systems in the green, red, and purple clusters (Walker Lane and the western Great Basin) were 160˚C, 158˚C, and 153˚C, respectively.

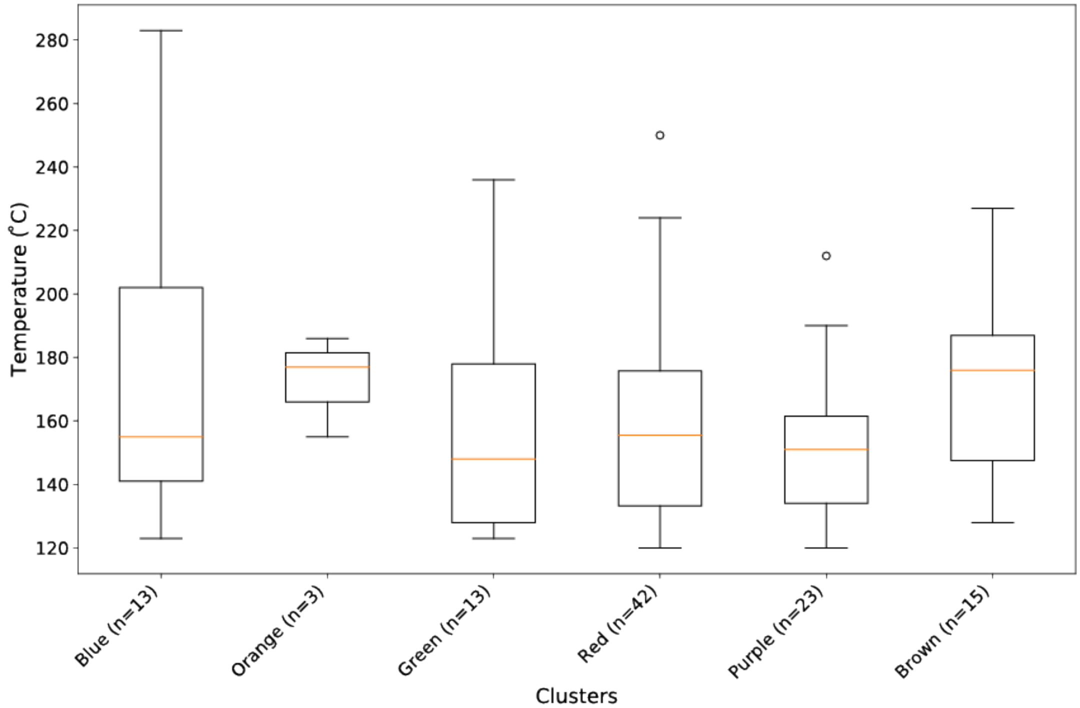


Figure 10: Box and whisker plot of the estimated temperatures for the known geothermal systems in each cluster.

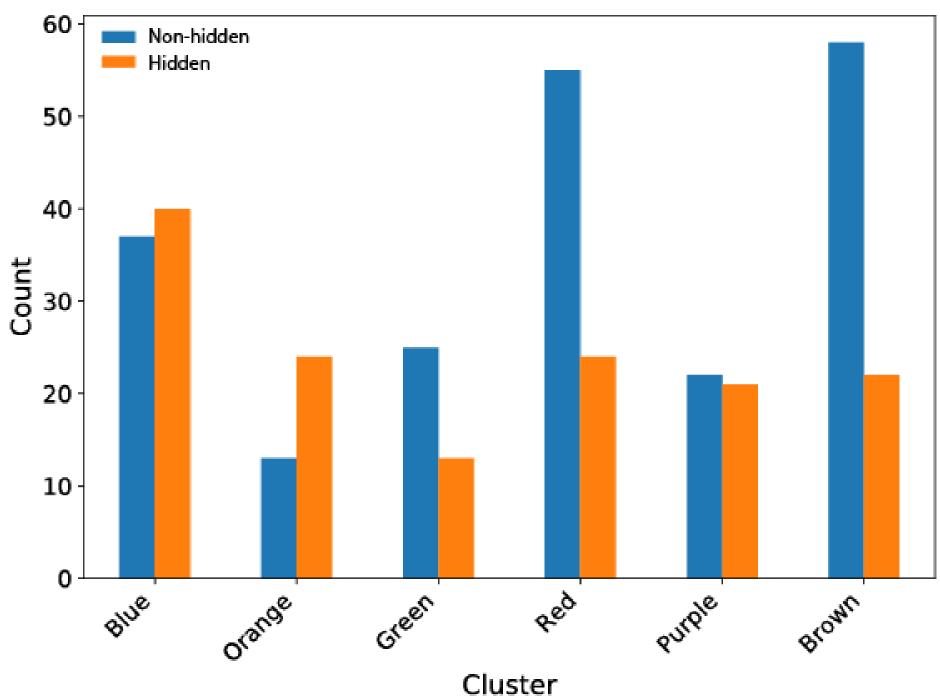


Figure 11: Number of hidden and non-hidden geothermal systems in each cluster.

It has been estimated that nearly three quarters of the geothermal resources in the Great Basin region lack surface expressions (e.g., Faulds et al., 2015). To understand the distribution of hidden and non-hidden geothermal systems in the clusters, the known geothermal systems were classified as hidden (no active surface thermal features) or non-hidden (has active surface thermal features such as a hot spring). Figure 11 shows the distribution of hidden and non-hidden geothermal systems in each cluster. The brown (eastern Great Basin), red (western Great Basin), and green (southwestern Walker Lane) clusters have significantly more non-hidden geothermal systems. This could suggest that these sub-regions have a higher potential for geothermal fluids to interact with the surface and form surface thermal features. In contrast, the orange (adjacent to the Snake River Plain) cluster has a higher proportion of hidden geothermal systems, which could suggest a higher likelihood for geothermal systems in this sub-region to be hidden. The blue (Quaternary volcanic fields) and purple (northeastern Walker Lane) have similar proportions of hidden and non-hidden systems.

There are not many known geothermal systems that are categorized as magmatic systems in the Great Basin region. Some of the magmatic systems that have been identified reside in the blue cluster, which is associated with Quaternary volcanic fields. However, there are also several that are in the green cluster, which is associated with the southwestern side of the Walker Lane. This suggests that while it might be limited, there may be a magmatic component in this Walker Lane sub-region.

Lastly, we identified the clusters where the current Great Basin geothermal power plants reside. The clusters with the highest concentration of actively producing geothermal power plants are the red cluster (western Great Basin) and the purple cluster (northeastern Walker Lane), each containing 27% of the power plants. The blue cluster (Quaternary volcanic fields) contains 19% and the brown (eastern Great Basin) cluster has 15% of the power plants. The green (southwestern Walker Lane) cluster and the orange cluster (adjacent to the Snake River Plain) have the lowest concentration, with 8% and 4% of the active power plants, respectively.

4.4 Implications for Modeling Geothermal Favorability

A cut-off of 120˚C is commonly used for assessing higher temperature geothermal systems (e.g., Hart-Wagoner et al., 2023), but here we utilized a lower temperature threshold to increase the number of systems utilized in the analysis. Even though some of these systems are lower temperature, having additional training sites in some of the areas with few identified higher temperature systems may help better characterize the geologic variability of geothermal systems in these regions. However, an analysis of just the higher temperature systems may provide more insight on the potential of the most productive geothermal systems in the study area.

Many of the higher temperature known geothermal systems are located in the western Great Basin. These higher temperature systems are commonly utilized in statistical techniques to develop relationships between geothermal favorability and these known geothermal systems. If these relationships are utilized to model geothermal favorability across the entire Great Basin, it is likely that the high contribution features, identified through this study, in the western Great Basin region are disproportionately favored in these models. Therefore, if these models are applied to areas such as the eastern Great Basin, geothermal favorability may not be modeled appropriately for that sub-region. This study is aligned with results from the Nevada PFA study area (e.g., Smith et al., 2021; Trainor-Guitton and Rosado, 2023) and suggests that the identified features may need to be weighted differently for sub-regions to more accurately model geothermal favorability across the sub-regions of the INGENIOUS Great Basin region study area. More work is needed to assess the high contributing features in each of these clusters or sub-regions and how they relate fundamentally to the conceptual model for Great Basin geothermal systems. Additionally, these results need to be assessed for how they can be integrated into the INGENIOUS regional play fairway workflow to model geothermal favorability across the Great Basin sub-regions.

5. Preliminary Conclusions

This preliminary PCA analysis has shown that while dimensionality reduction can be applied, there are still many principal components required to explain the variance of the dataset. Additionally, the k-means clustering analysis utilized six clusters, and independent of assigning geologic domains to the known geothermal systems, the known geothermal systems cluster geographically and align with various geologic sub-regions of the Great Basin region. These include sub-regions such as the Walker Lane, extensional western Great Basin region, broad lower strain region in the eastern Great Basin, the area adjacent to the Snake River Plain, and Quaternary volcanic fields. The identified clusters were also assessed to discern the key contributing features and their positive and negative relationships to better assess geothermal variability between the clusters and sub-regions. The identified clusters also provide insight into the temperature distributions, proportion of hidden and non-hidden geothermal systems, and geothermal potential in each sub-region. Finally, the results of this study suggest that features may need to be weighted differently for individual sub-regions to more accurately model geothermal favorability across the sub-regions of the Great Basin.

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