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ALGAIAR, M.

2025

This output file contains the extended abstract and slides presented at the conference which have been incorporated into a single file.

Improving Geothermal Resource Assessment: A Data-Driven Approach to Chemical Geothermometry Using Deep Learning

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Robert Gordon University

Summary

This study presents a deep learning model trained on a dataset of 674 water samples from Nevada to predict geothermal reservoir temperatures. The model outperforms traditional geothermometers and other machine learning models, achieving high accuracy and demonstrating global applicability when tested on samples from different geothermal fields around the world.

Introduction

Geothermal energy is a promising source of renewable, clean and sustainable energy. Accurate prediction of subsurface temperatures is critical for geothermal exploration and development. Traditionally, this has been done using classical geothermometers, which rely on the chemical equilibrium between reservoir fluids and host rocks. However, these methods can be potentially unreliable due to factors such as fluid mixing and degassing. This study presents a novel data-driven model designed to overcome these limitations and provide more accurate temperature predictions for diverse geothermal systems.

The data-driven model harnesses the power of machine learning to analyze extensive hydrogeochemical data and identify patterns that may be missed by traditional methods. This innovative approach was trained and validated using a comprehensive dataset of 674 water samples from Nevada, a region known for its significant geothermal potential and diverse geological settings. The study also explores the geological and hydrogeological characteristics of Nevada's geothermal systems, examining factors such as fault systems, groundwater flow patterns, and water chemistry.

Methodology

Recognizing the limitations of classical geothermometers and addressing the challenge of missing subsurface temperature measurements in the Nevada water sample dataset, subsurface temperature was inferred using multiple techniques including classical and multicomponent geothermometry, regional thermal database extrapolation, and an existing machine learning geothermometer. This comprehensive approach ensured a robust dataset for training the machine learning model. After data preprocessing and exploratory data analysis, including feature selection and data clustering, the deep neural network model outperformed other machine learning models tested (Random Forest, XGBoost, and Back-Propagation Neural Network), achieving high accuracy (R^2 = 0.978) and low error rates on both the training and test datasets, as shown in Figure 1. Validation with 42 new well samples from different geothermal fields around the world confirmed its applicability and reliability in different geological environments.

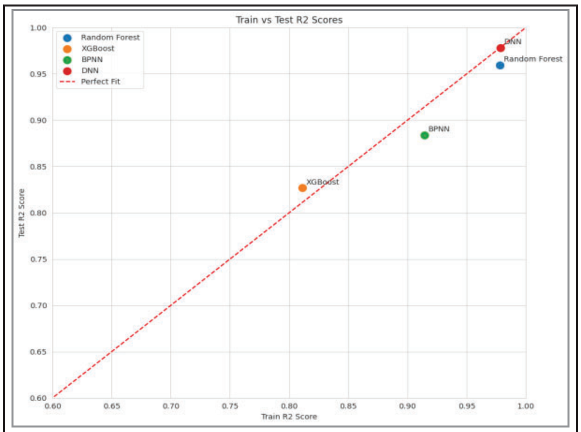

Figure 1: Train vs Test R^2 scores for adopted models

Conclusions

This study successfully developed and validated a novel deep learning model for predicting geothermal reservoir temperatures using geochemical data. The model was trained on a comprehensive dataset of 674 water samples from Nevada, addressing the limitations of traditional geothermometers and leveraging the power of machine learning to identify complex patterns in hydrogeochemical data. The deep learning model outperformed other machine learning

models, including Random Forest, XGBoost, and Back-Propagation Neural Networks, achieving high accuracy ($R^2 = 0.978$) and low error rates. The study addressed the challenge of missing subsurface temperature measurements in the dataset by employing a multi-pronged inference strategy that combined classical geothermometers, multicomponent geothermometry, regional thermal database extrapolation, and an existing machine learning geothermometer. This approach ensured a robust and reliable dataset for training and validation of the deep learning geothermometer. Furthermore, the global applicability of the model was demonstrated by testing it on 42 new well samples from different geothermal fields around the world, demonstrating its ability to perform well in different geological environments. This approach represents a significant advance in chemical geothermometry, providing a more accurate, efficient, and globally applicable tool for predicting subsurface temperatures in geothermal exploration and reservoir characterization. Future research will focus on expanding the dataset, incorporating advanced feature engineering, and developing a user-friendly platform to disseminate the model's capabilities and further advance geothermal research and investment opportunities.

Keywords

Geothermal Resource Exploration, Hidden/Blind Geothermal Resources, Artificial Intelligence, Machine Learning, Deep Learning

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23–25 June ‘25 • Virtual

Improving Geothermal Resource Assessment: A Data-Driven Approach to Chemical Geothermometry

Mahmoud AlGaiar – Robert Gordon University

Geothermal Overview

1

Renewable Source

Geothermal energy is derived from Earth's heat, providing stable, sustainable power.

power.

2

Global Growth

Geothermal energy could meet 15% of global electricity demand by 2050, with a potential

potential global capacity of 800 gigawatts - equivalent to the current electricity demand of the

demand of the US and India combined (IEA 2025).

3

Key Countries

Significant in USA, Indonesia, Philippines, Türkiye, and New Zealand.

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Exploration Challenges

1

Financial Risks

High costs during predevelopment stages, including surface surveys and exploratory drilling.

2

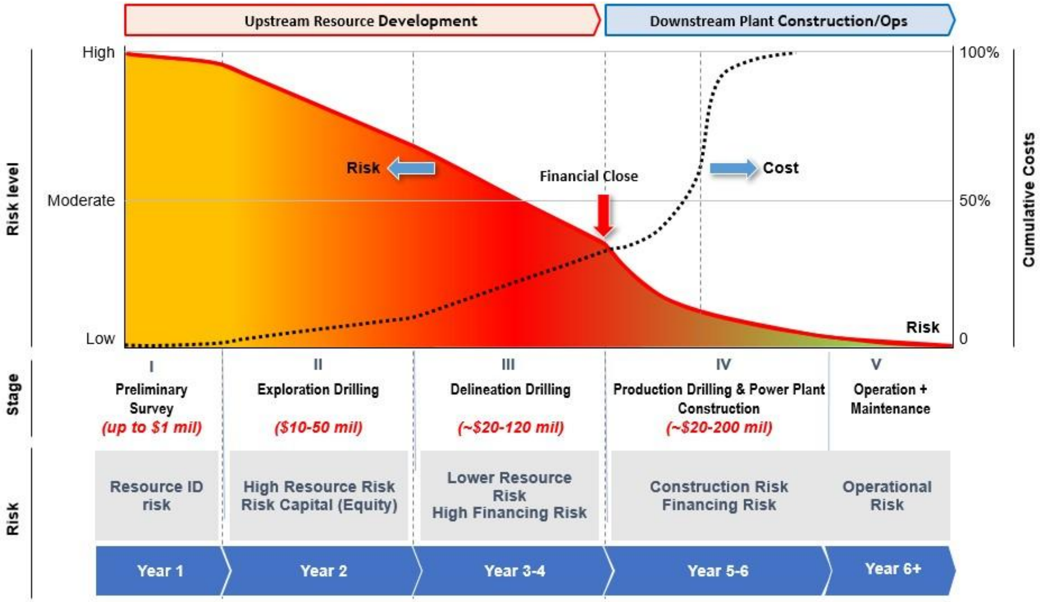
Hidden Resources

Difficulty in identifying blind geothermal resources without surface manifestations.

3

Expert Reliance

Traditional methods heavily depend on expert expert knowledge, leading to uncertainties. uncertainties.



The stages of the geothermal development project and its risk levels (Gehringer and Loksha, 2012).

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Geochemical Analysis

Cost-Effective

Geochemical data from groundwater samples are crucial in early exploration stages.

Insightful

Provides valuable information on subsurface characteristics and reservoir properties.

Analytical

Helps determine reservoir temperature, heat flow, and potential for energy extraction.

Geothermometry

1

Classical Geothermometers

function based on temperature-dependent mineral-fluid equilibrium reactions, primarily utilizing silica concentrations and cation ratios (Na-K, Na-K-Ca, K-Mg) in geothermal waters.

2

Multicomponent Geothermometry

analyzes the equilibrium between multiple minerals, focusing on the convergence of mineral saturation indices at the true reservoir temperature.

3

Data-Driven Geothermometers

a modern approach that utilizes machine learning and statistical methods to establish correlations between fluid chemistry and reservoir temperatures.

Methodology

1

Comprehensive Dataset

Utilizing water samples from diverse geothermal regions in Nevada

2

Advanced Methodology

Integrating classical geothermometers, multi-component geothermometry, and ML

3

Improved Accuracy

Demonstrating excellent performance, explaining variance in training and test data

4

Global Applicability

Evaluation on new well samples from different geothermal fields worldwide

Exploratory Data Analysis

1

Extensive Dataset

Analysis of over 14,400 geochemical samples from the Great Basin Groundwater Groundwater Geochemical Database. This vast collection of information forms the forms the backbone of the platform's predictive capabilities.

2

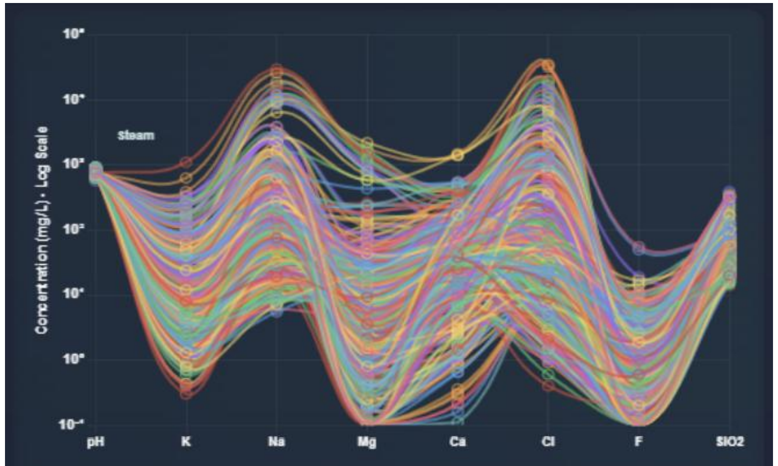
Data Integrity

To ensure data quality, the model performs a charge balance error calculation, rejecting samples outside the acceptable range of ±5%. This rigorous approach guarantees the reliability of the input data.

3

Feature Selection

Through exploratory data analysis, eight key features were identified as strong strong influencers of temperature: **potassium**, **sodium**, **magnesium**, **calcium**, **calcium**, **chloride**, **fluorine**, **silica**, and **pH**. These elements form the core of aiION's of aiION's predictive model.



Training data statistics

Parameter	Mean	Std	Min	Max	25%	75%
pH	7.80	0.50	5.70	9.30	7.50	8.00
K	22.98	66.61	0.30	1100.00	3.43	12.00
Na	544.54	2269.21	5.50	30000.00	31.00	210.00
Mg	45.47	199.42	0.01	2200.00	2.30	19.00
Ca	63.24	119.82	0.10	1500.00	17.00	64.00
Cl	642.03	2953.29	0.40	35000.00	10.00	118.50
F	1.58	3.57	0.03	55.30	0.20	1.58
SiO_2	57.42	52.26	14.00	389.00	31.00	62.00
T	86.14	30.39	36.40	218.20	66.40	97.80

Data Processing

Data Transformation

Employing various data transformation methods, including z-score, logarithmic transformation, and quantile normalization. These techniques optimize model performance and ensure accurate predictions.

Clustering Analysis

Utilized clustering techniques such as K-as K-means and Hierarchical Clustering Clustering to identify patterns within within the dataset. This approach helps helps in understanding the underlying underlying structure of the geochemical geochemical data.

ML Model Development

Several machine learning algorithms were evaluated to determine each algorithm's algorithm's predictive ability and to determine the best model.

1. **Random Forest (RF)**
   Ensemble learning method using multiple decision trees
2. **Gradient Boosting (XGB)**
   Builds new trees sequentially to reduce bias from previous trees
3. **Artificial Neural Network (ANN)**
   Simple backpropagation neural network with four layers
4. **Deep Neural Network (DNN)**
   More complex architecture with three three hidden layers and advanced techniques

DNN Model Performance Metrics

0.9784

DNN R^2 (Train)

Coefficient of determination for training data

0.9783

DNN R^2 (Test)

Coefficient of determination for test data

4.0097

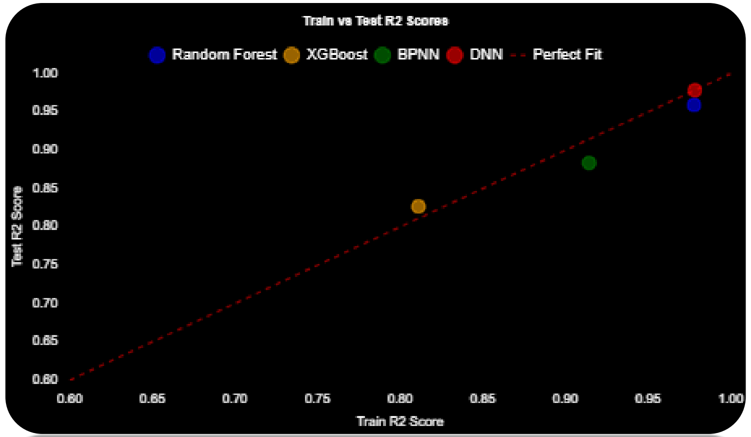
DNN RMSE

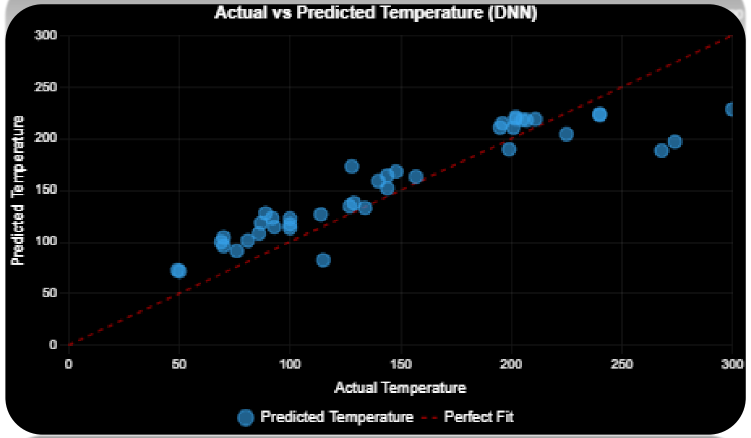
Root Mean Square Error for test data

2.6363

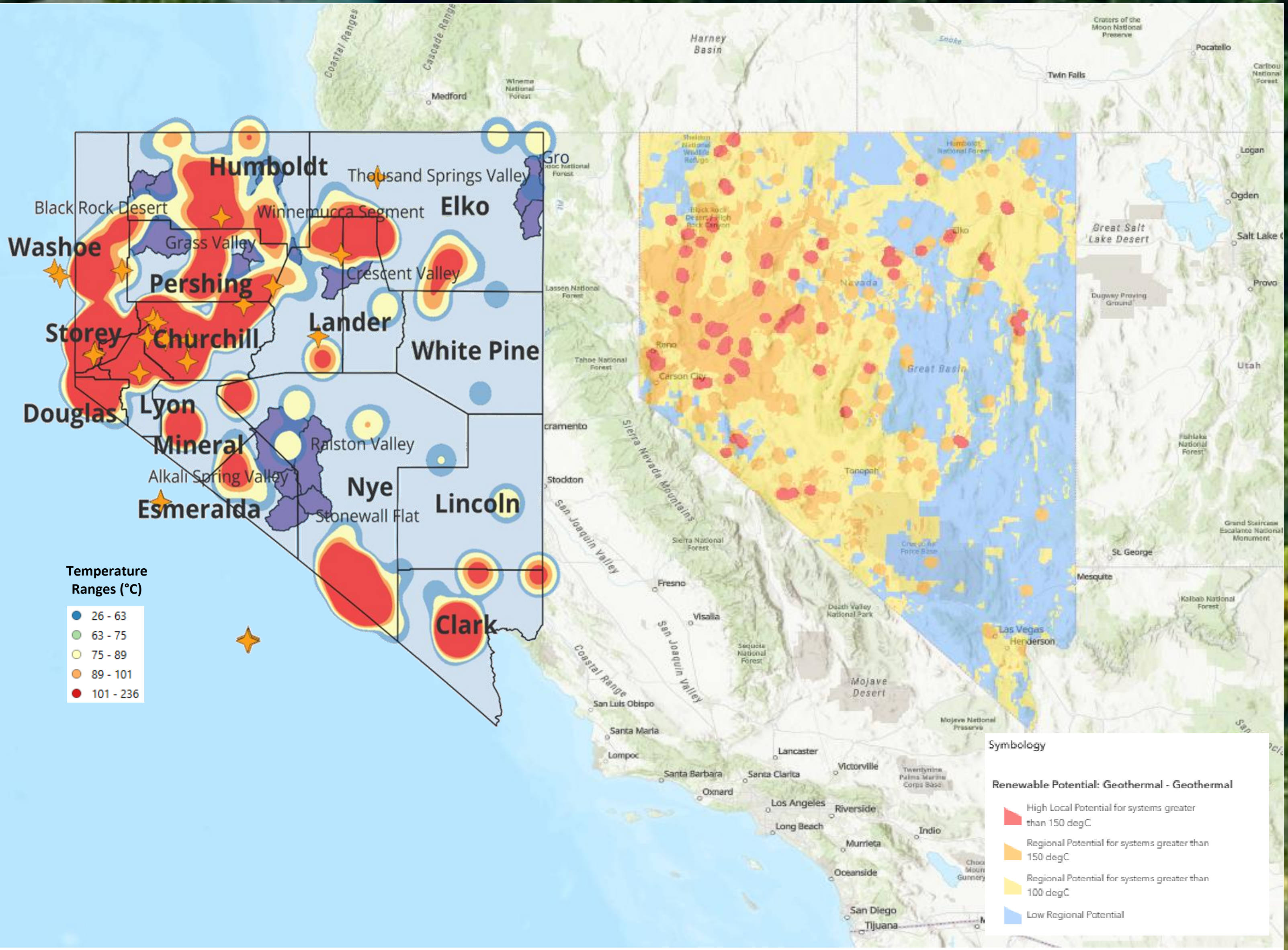
DNN MAE

Mean Absolute Error for test data

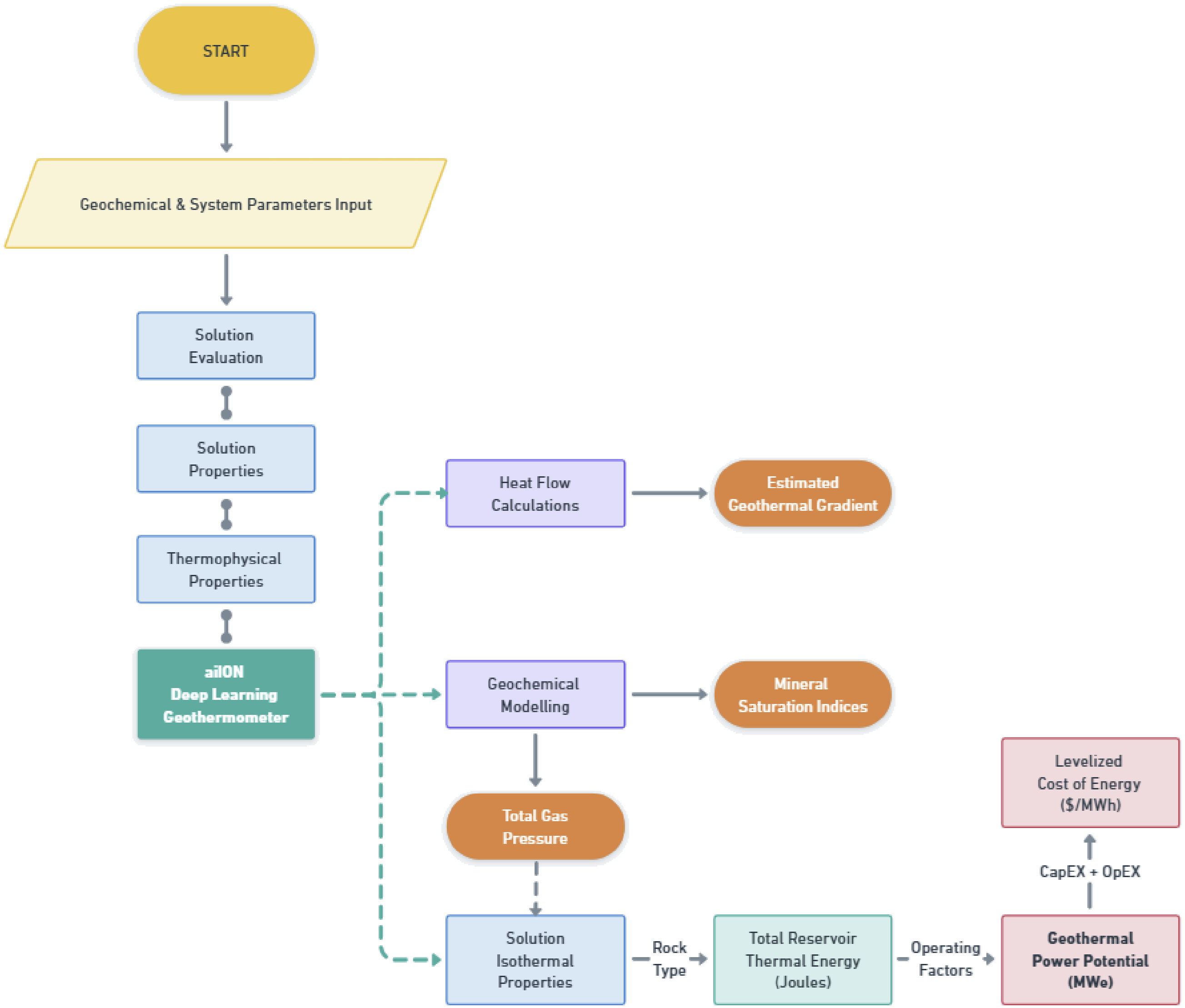




Nevada Geothermal Potential Map



ailON Software Platform



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Solution Properties Module

Classification

Categorize water based on its properties, properties, including **class**, **type**, and and **description**. This classification helps helps in understanding the nature and and origin of the geothermal fluid.

Chemical Equilibrium State

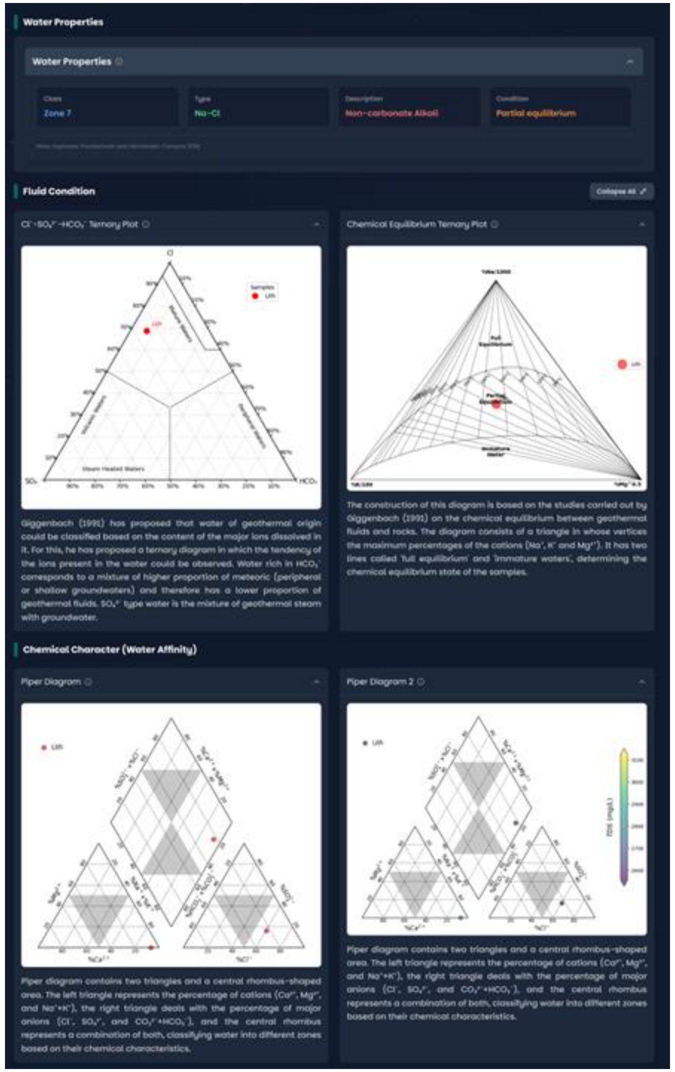
Determine the chemical equilibrium state of the water, providing insights into its **maturity** and potential for geothermal energy production.

Hydrogeochemical Processes

Understanding the mechanisms controlling water chemistry. It helps helps identify the dominant processes processes affecting the geothermal geothermal fluid composition and controlling water chemistry and rock rock weathering, categorizing samples samples into precipitation-dominated, dominated, rock weathering-dominated, and evaporation/ crystallization-controlled types.

Trace Elements Analysis

Ternary Diagrams to visualize the relationships between Cl^-, B, and F^- F^- concentrations and Cl^-, B, and Li^+ Li^+ concentrations in the geothermal geothermal fluid. This analysis helps in helps in understanding the fluid's origin origin and evolution.



Geochemical Modelling Module

Molality and Moles

Lists the molality and moles of various elements, including C, Ca, Cl, F, K, Mg, Na, S, and Si.

Solution Description

Provides detailed information including Sample ID, pH, pe, Activity of water, Ionic strength, Mass of water, Total alkalinity, Total CO_2, and Electrical balance.

Species Distribution

Lists the molality, activity, and log activity of various species, such as OH^-, H^+, H_2O, HCO_3^-, Ca^{2+}, Cl^-, F^-, K^+, Mg^{2+}, Na^+, SO_4^{2-}, and SiO_2.

Mineral Saturation Analysis

This module provides a comprehensive comprehensive summary of mineral saturation indices, indicating the extent of extent of their saturation in the geothermal geothermal fluid. This information is crucial crucial for understanding the chemical chemical equilibrium of the system.

Gas Fugacity and Pressure

ailON calculates and reports the fugacity and partial pressure of gases in the solution, such as CO_2 and H_2O. This data is essential for understanding the behavior of gases in the geothermal reservoir.

Thermophysical Module

1

Comprehensive Solution Properties

aiION calculates crucial thermophysical properties including solution quality, density, specific volume, dynamic viscosity, thermal conductivity, internal energy, entropy, enthalpy, and heat capacity.

2

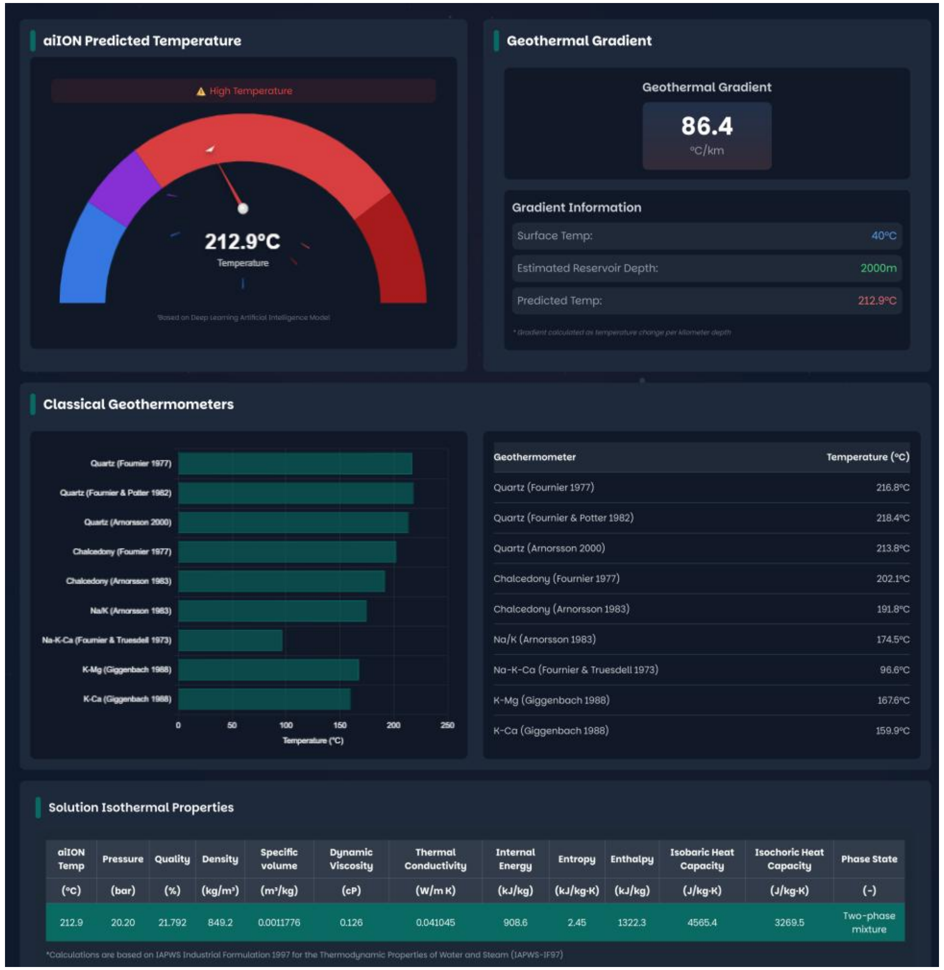
Geothermal Gradient Analysis

Computing effective thermal conductivity and geothermal gradients, providing insights into the heat distribution within the reservoir.

3

Heat Flow Assessment

aiION calculates heat flow, a critical parameter for understanding the energy potential of a geothermal system.



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Geothermal Potential Module

Thermal Energy Calculation

Computes total thermal energy of the reservoir

Power Potential Estimation

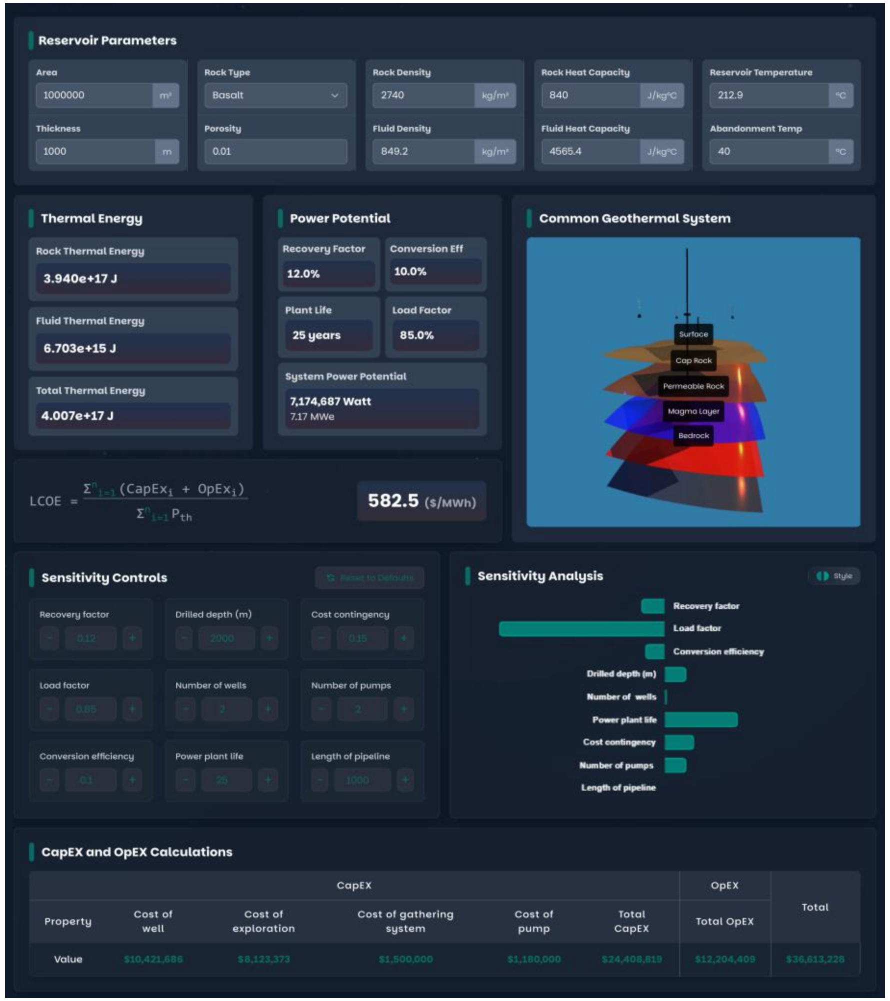
Calculates potential power output in Watts and MWe

Economic Viability Analysis

Calculation of CapEX & OpEX and determining the LCOE

Sensitivity Analysis

Allows adjustment of key parameters for scenario planning



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Implications for Geothermal Exploration

1 **Improved Accuracy**

ailON provides reliable temperature predictions for geothermal reservoirs

2 **Cost-Effective Exploration**

Reduces the need for expensive drilling and testing in early exploration stages

3 **Blind System Identification**

Enhances ability to locate and assess "blind" geothermal systems without surface manifestations

4 **Resource Assessment**

Facilitates more accurate estimation of geothermal potential in unexplored areas

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