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Review

Machine Learning for Geothermal Energy Systems: Prediction, Optimization, and Physics-Informed Hybrid Methods

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Abstract

Geothermal energy is a clean, stable, and low-carbon renewable resource with increasing strategic importance in sustainable energy transitions. In recent years, machine learning has been progressively applied in geothermal systems, including resource exploration, reservoir characterization, drilling and operational optimization, heat-transfer performance prediction, and ground source heat pump (GSHP) control. Machine learning enables high-dimensional data mining, complex mapping, and surrogate modeling. While it can often deliver higher efficiency and accuracy compared to conventional methods, these advantages are not absolute; rather, they are highly contingent upon the quality and scale of the dataset, the rigorousness of the validation method, and the appropriateness of the selected algorithm. This review systematically summarizes major machine learning applications in geothermal energy, highlighting representative methods, data sources, target tasks, and research features. It identifies critical limitations in current studies, including dataset scale and quality, model generalization, physical consistency, interpretability, and deployment feasibility. The review further emphasizes the evolution of geothermal machine learning from pointwise prediction tools to frameworks supporting intelligent analysis, optimization, and decision-making. Future directions include multi-source heterogeneous data fusion, embedding of physical mechanisms, interpretable modeling, and integration with digital twin systems. These approaches aim to shift machine learning from high-accuracy prediction toward trustworthy and deployable decision support for geothermal energy systems.

Keywords: geothermal energy; machine learning; reservoir characterization; ground source heat pump

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1. Introduction

Geothermal energy is increasingly recognized as a stable and dispatchable renewable energy source for low-carbon heating, cooling, and power generation [1]. Compared with wind and solar energy, geothermal systems can provide relatively continuous energy output and therefore have strong potential for supporting low-carbon energy transitions. Due to these advantages, geothermal energy has been widely applied in district heating, combined building heating and cooling, and power generation [2]. However, geothermal development remains challenging because subsurface systems are highly heterogeneous,

strongly nonlinear, and governed by complex multi-scale thermal–hydraulic–geological interactions. As a result, key tasks such as resource exploration, reservoir characterization, production forecasting and operational optimization are often affected by large uncertainty, high inversion cost and limited real-time decision support.

Traditional geothermal studies mainly rely on geological surveys, geophysical exploration, hydrogeochemical analysis, statistical regression, and numerical simulation. These methods are indispensable for mechanism-based interpretation. Nevertheless, they are still limited in processing high-dimensional heterogeneous data, representing complex nonlinear relationships, and supporting rapid decision-making. In particular, tasks such as geothermal target identification, reservoir parameter inversion, real-time drilling control, production–injection optimization and long-term system management often suffer from high computational cost, long modeling cycles and low efficiency.

With the rapid development of machine learning, geothermal studies are moving beyond isolated parameter prediction toward broader tasks such as resource prospectivity assessment, dynamic reservoir management, multi-objective operational optimization, and physics-informed modeling [3]. Machine learning models can learn useful patterns from geological, geophysical, logging, hydrochemical, operational, and simulation data, thereby supporting faster prediction, classification, inversion, and decision-making [4,5]. However, this progress has also revealed several unresolved issues, including limited sample size, uneven data distribution, weak cross-site generalization, insufficient physical consistency, and uncertain engineering reliability under extreme operating conditions. First, geothermal data often have limited sample size, uneven spatial distribution, high labeling cost, and strong heterogeneity. This weakens the basis for model training. Second, many high-accuracy models are built on data from specific regions, small samples, or numerical simulation datasets. Their cross-site generalization and engineering applicability still need validation. In addition, purely data-driven models often show clear limitations in physical consistency, interpretability, and robustness under extreme operating conditions. In high-risk and high-investment geothermal development, black-box prediction alone is not sufficient for real engineering needs. These limitations indicate that geothermal machine learning is shifting from accuracy-oriented prediction toward reliability-oriented intelligence, where physical consistency, uncertainty awareness, transferability, and deployment readiness become equally important.

While several existing reviews have summarized machine learning applications in geothermal energy, they typically focus on specific sub-domains or provide historical overviews restricted to earlier research phases. Compared with the broader existing literature, the novelty of this review lies in a new comprehensive classification and analysis framework built upon three distinct perspectives. First, rather than isolating deep or shallow systems, it establishes a full-process framework that unifies resource exploration, reservoir characterization, operational optimization, and shallow heat pump systems under a single intelligent development pipeline. Second, it provides a unique method–scenario matching analysis, systematically comparing which machine learning algorithms are most robust for specific geothermal data structures, sample sizes, and engineering constraints. Third, it specifically highlights the critical ongoing transition from purely data-driven black-box models to physics-informed, uncertainty-aware, and digital-twin-oriented geothermal intelligence, addressing the exact bottlenecks that currently hinder practical engineering deployment.

This paper establishes a comprehensive analysis framework to clarify these concepts. Table 1 summarizes the research framework and module overview of this review. In addition, Figure 1 illustrates the schematic framework of machine learning applications in

geothermal energy. These diagrams aim to visually present the core logic and classification system of this study.

Table 1. Research framework and module overview of this review.

Geothermal Task	Core Issue	Common Methods	Review Focus
Resource exploration	Anomaly identification; potential zonation	RF, XGBoost, SVM, clustering	Emphasis on multi-source data and spatial validation
Reservoir characterization	Temperature and thermophysical property prediction	Tree-based models, SVR, shallow neural networks	Emphasis on sample size and generalization boundaries
Development optimization	Drilling prediction; production–injection optimization	LSTM, surrogate models, active learning	Emphasis on real-time capability and engineering constraints
Heat transfer and heat pumps	Performance prediction; control optimization	XGBoost, RF, time-series models	Emphasis on long-term operation and transferability
Emerging methods	Physical consistency and trustworthy prediction	PINN, neural operators, hybrid models	Emphasis on mechanism integration and field validation

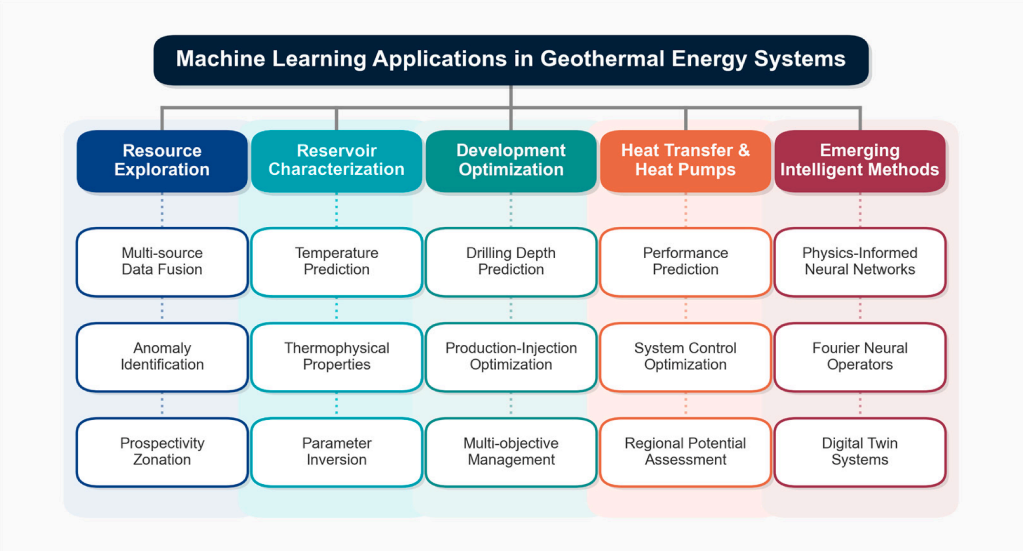


Figure 1. Schematic framework of machine learning applications in geothermal energy.

2. Methodology

2.1. Search Strategy and Literature Screening

A systematic literature search was conducted adhering to the PRISMA 2020 guidelines. The literature identification relied on a rigorous dual-path strategy: a primary database search and a supplementary citation snowballing process.

The primary search was performed in the Elsevier database (including ScienceDirect and Scopus) covering the period from January 2021 to 2026. To capture the full scope of this comprehensive review, the search employed the following Boolean logic strictly within the Title, Abstract, and Keywords fields: (“machine learning” OR “deep learning”) AND (“geothermal reservoir” OR “geothermal energy” OR “ground source heat pump”). This search yielded an initial pool of 223 records.

2.2. Inclusion/Exclusion Criteria and Snowballing

The 223 records were initially screened based on title and abstract relevance. Subsequently, 103 full-text articles were assessed for eligibility based on strict criteria. Studies

were excluded if they: (1) did not explicitly couple machine learning with geothermal applications; (2) were solely based on traditional numerical simulations without data-driven models; or (3) lacked comprehensive data. This primary search path yielded 38 core articles.

To ensure maximum comprehensiveness and capture pivotal studies not indexed in the primary precise search, a rigorous citation snowballing method (backward reference tracking) and manual retrieval were applied. This supplementary process captured additional high-quality articles from other publishers, essential regional studies, and fundamental background reports. Through this method, an additional 28 records were evaluated and incorporated. Ultimately, a total of 66 qualified references were synthesized in this review, as detailed in the PRISMA flow diagram (Figure 2).

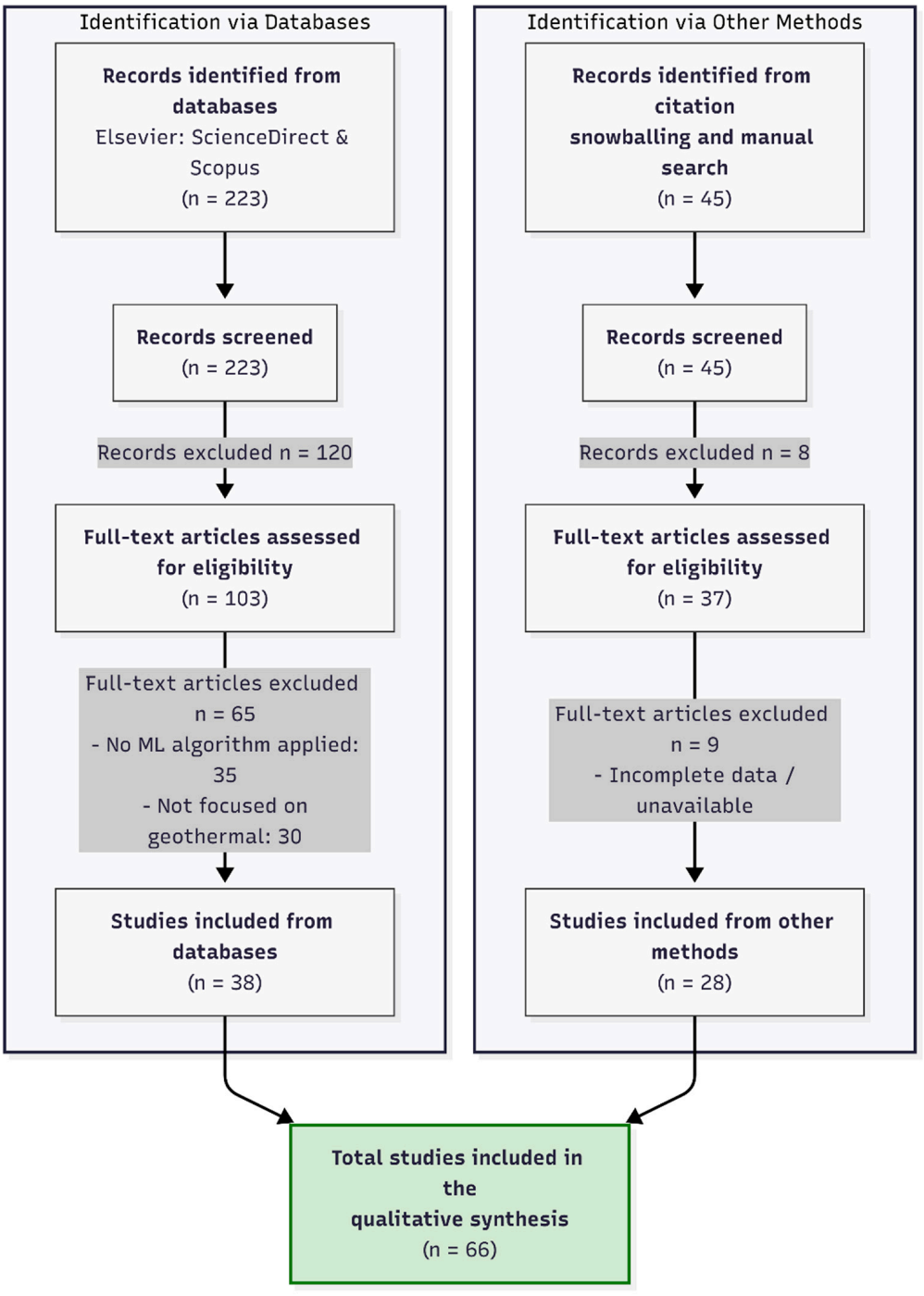


Figure 2. PRISMA flow diagram of the literature screening and selection process.

2.3. Analysis of Literature Representativeness and Potential Biases

The literature selection followed a systematic approach. However, the current body of research contains potential biases. Acknowledging these biases helps to assess the representativeness of the reviewed studies accurately.

First, a clear regional bias exists. Many highly accurate machine learning models rely on datasets from a few well-documented geothermal sites. These sites include the United States FORGE site, specific sedimentary basins in China, and Western Anatolia in Turkey. This geographical concentration limits the cross-site transferability of these models. They may not work well in regions with different geological or hydrogeochemical settings.

Second, publication bias is an inherent limitation in the current literature. Studies predominantly report successful and highly optimized models. These models usually achieve excellent predictive metrics like high R-squared and low root mean square error values. Conversely, negative results and algorithmic failures are rarely published. Models that underperform under complex and noisy field conditions are also missing from the literature. This creates an overly optimistic view of machine learning applications in geothermal engineering.

Finally, a notable research-topic bias is evident across the selected literature. Most current studies focus heavily on localized and high-yield tasks. Examples include reservoir temperature prediction, drilling depth regression, and short-term performance optimization of ground source heat pumps. In contrast, research on long-term environmental risk assessments remains scarce. Full life-cycle economic analyses and predictions of long-term equipment scaling and corrosion are also lacking. Acknowledging these biases is crucial for critically evaluating the current state of the art. It also guides future research toward more balanced and globally representative frameworks.

3. Machine Learning for Geothermal Resource Exploration

Geothermal resource exploration is the first step in geothermal development. Its core goals are to delineate favorable geothermal zones and predict geothermal potential. Traditional exploration depends on the integrated analysis of geological, geophysical, and geochemical data. These methods often have low efficiency and strong subjectivity. Machine learning can build nonlinear relationships from multi-source data. It can therefore identify geothermal anomalies and delineate exploration targets more efficiently [6–8].

In the exploration of fault-controlled geothermal systems, Liao et al. [9] used the unsupervised NMFk method. They analyzed 364 datasets of geothermal fluid hydrochemistry, heat flow, and distance to faults from the Chenzhou–Huizhou region in Southeast China. The geothermal fluids were divided into three groups. Type B showed the highest exploration potential. It was characterized by deep circulation, high reservoir temperature, and strong sealing. It was mainly controlled by NW-trending faults and high-heat-producing granite. Based on these results, the authors established a conceptual genetic model for fault-controlled geothermal systems. The approach greatly reduced exploration cost and improved target screening efficiency. Similarly, Ahmmed et al. [10] demonstrated the value of combining machine learning with shallow groundwater chemistry to identify geothermal prospects in the Great Basin, USA. These works provide new machine learning paradigms for regional geothermal exploration.

Li et al. [11] focused on geothermal exploration in Xianning, Hubei Province. They developed a geothermal potential prediction model based on a stacking ensemble method. By combining random forest and a multilayer perceptron, they identified geothermal gradient, reservoir temperature, gravity anomaly, and deuterium-inferred recharge elevation as the core predictors of geothermal potential. They then generated a geothermal potential zonation map and an exploration target map for the study area. The authors preprocessed

12 geological feature layers on a GIS platform. They trained four models in parallel, including linear regression, a deep neural network, a multilayer perceptron, and random forest. They then integrated random forest and multilayer perceptron through stacking and built an RF-MLP ensemble model. This model clarified the key geological factors controlling geothermal distribution in Xianning. It also produced the final spatial prediction results.

Figure 3 shows the full workflow and final spatial prediction results for geothermal potential in the Xianning area. The figure shows a complete pipeline. It starts with multi-source geological feature input, continues with model training, and ends with geothermal potential mapping. It also directly demonstrates the value of machine learning in regional target screening.

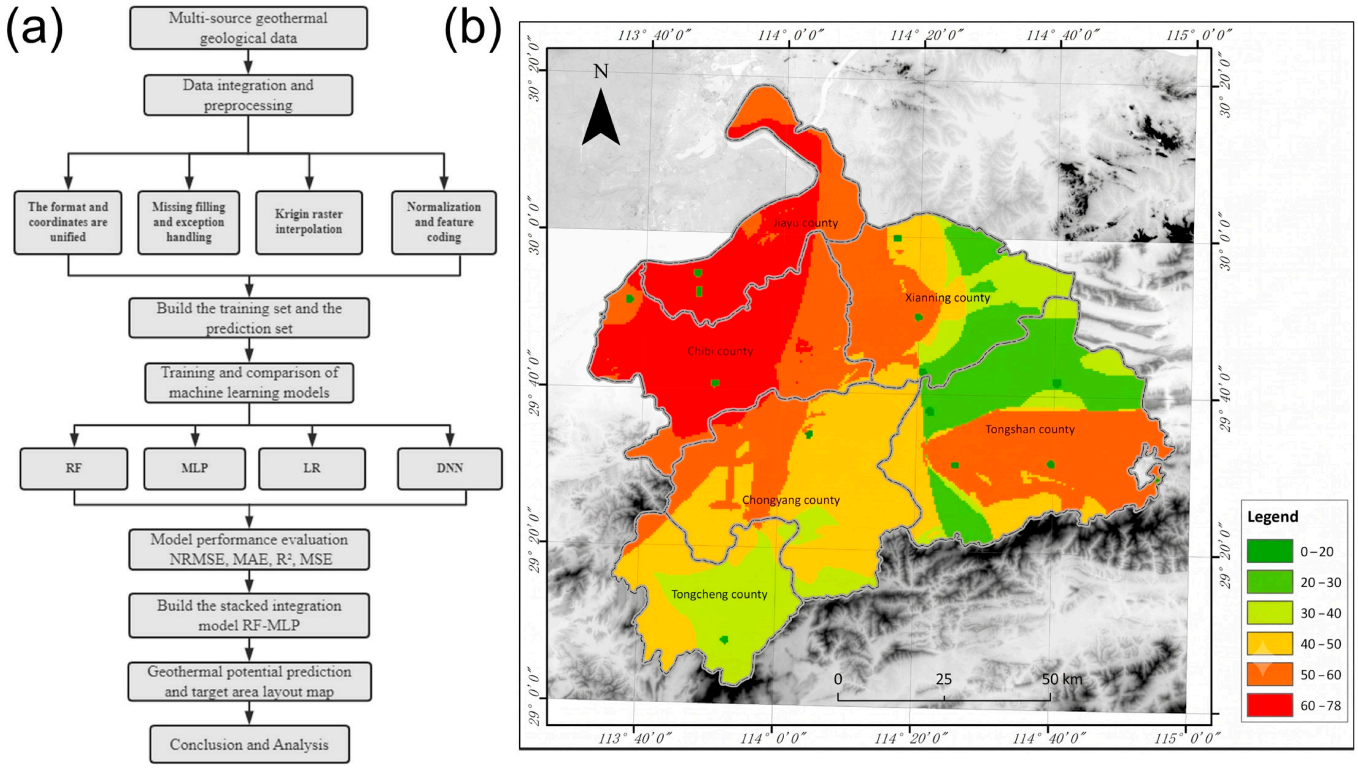


Figure 3. (**a**) Workflow of the study; (**b**) predicted geothermal potential distribution using the stacking ensemble model [11]. Reproduced from Ref. [11] under a Creative Commons Attribution (CC-BY) license.

For enhanced geothermal systems (EGSs), related studies have developed deep learning models to predict output temperature and fracture permeability under dynamic injection rates [12]. These models provide an efficient tool for dynamic parameter monitoring in EGS reservoirs. It is also worth noting that some studies have shown that more complex machine learning strategies do not always yield higher prediction accuracy in geothermal tasks. Overly complex models may reduce predictive reliability because of overfitting and related problems [13]. This finding suggests that researchers should balance model complexity and generalization ability. Blindly stacking algorithms is not always beneficial.

In geothermal prospectivity mapping, Li et al. [14] systematically reviewed research progress in the era of big data and machine learning. They compared traditional play fairway analysis with machine-learning-enhanced play fairway analysis (ePFA). They also used a case study from Texas, USA, to verify the advantages of ePFA. Their results showed that machine learning can effectively handle multi-source, high-dimensional, and nonlinear geothermal datasets. It has great potential to reduce exploration time, cost, and drilling risk [14–17]. The review by Li et al. [14] summarized the main controlling factors

of geothermal resource distribution, the key issues and techniques in spatial data analysis, and the strengths and weaknesses of different modeling methods. It also clarified the future prospects of machine learning in geothermal prospectivity mapping. As shown in Figure 4, the machine-learning-enhanced prospectivity analysis framework retains the integrated logic of traditional PFA for identifying controlling factors. At the same time, it strengthens the recognition of high-dimensional nonlinear features through spatial data-driven modeling. The workflow comparison in Figure 4 shows that ePFA has clear advantages in data integration efficiency, prediction automation, and target screening accuracy.

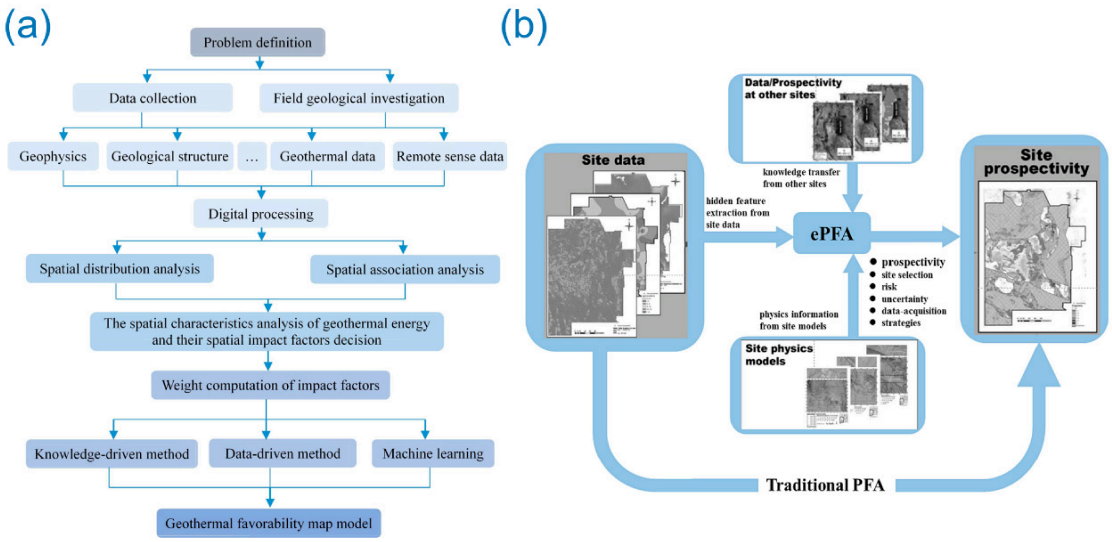


Figure 4. (**a**) Workflow of geothermal prospectivity prediction based on spatial data analysis; (**b**) comparison between ePFA and traditional PFA [14]. Reproduced with permission from Ref. [14]. Copyright 2026, Elsevier.

To move beyond isolated case studies, it is essential to compare these algorithms and understand their suitability for different geological data structures. Unsupervised methods like NMFk are particularly well-suited for early-stage exploration where labeled data such as confirmed well production or reservoir temperature is scarce or absent, allowing for the unbiased discovery of hidden hydrogeochemical groupings. However, their practical application is often limited by the difficulty of quantitative validation without ground truth. For supervised tasks, tree-based algorithms including random forest and XGBoost are highly robust against the outliers and missing values typical of heterogeneous geological datasets, while simultaneously providing valuable feature importance metrics. Conversely, multilayer perceptrons excel at capturing deep, high-dimensional nonlinear mappings but are highly data-hungry and prone to overfitting on the small sample sizes common in geothermal exploration. Stacking ensemble methods like the previously mentioned RF-MLP model effectively mitigate this by combining the structural robustness of decision trees with the representational power of neural networks, though this comes at the cost of reduced interpretability and higher computational demand. Finally, spatial frameworks like ePFA are uniquely designed for multi-layered GIS data, explicitly addressing spatial associations that standard tabular models miss; nevertheless, they are often limited by spatial autocorrelation, which can lead to overestimating model generalization if spatial cross-validation is not strictly enforced.

Overall, machine learning provides a more efficient way to process data and identify patterns in geothermal resource exploration. It is especially suitable for integrating multi-source information, handling coupled controlling factors, and rapidly evaluating regional potential. However, three major problems remain. First, most studies are based on data

from only one region. Their spatial coverage is limited. Second, spatial variables often show strong autocorrelation. Randomly splitting training and test sets may overestimate model generalization. Third, geological interpretation of prediction results is still often insufficient. Future work should move beyond high-accuracy local zonation. More attention should be given to cross-regional transferable identification and interpretable genetic modeling.

4. Machine Learning for Geothermal Reservoir Characterization and Parameter Prediction

Reservoir characterization and parameter prediction are core steps in geothermal development. They directly affect resource assessment, development planning, and long-term production management. Geothermal reservoirs are usually controlled by lithology, structure, porosity and permeability, fracture networks, hydrogeochemical conditions, and reservoir boundaries. Traditional methods for obtaining these parameters mainly rely on drilling tests, core experiments, thermal response tests, and numerical inversion. These methods are costly, time-consuming, and difficult to scale up rapidly. Machine learning offers a new solution. It builds mappings between reservoir parameters and observable features. This allows key parameters to be estimated more quickly.

4.1. Reservoir Temperature Prediction

For reservoir temperature prediction, many studies have used hydrogeochemical indicators, well depth, ion concentrations, and structural background as inputs for regression models [18,19]. Compared with conventional geochemical thermometers, machine learning models can integrate more variables and learn more complex nonlinear relationships. They therefore often show higher accuracy on specific datasets. Some studies have also used SHAP or sensitivity analysis to identify key controlling variables. This improves model interpretability [20].

Ibrahim et al. [21] studied geothermal systems in Western Anatolia, Turkey. Based on 84 hydrogeochemical samples, they developed five machine learning models, including NGB, ELM, GMDH, GRNN, and BPNN. The NGB model achieved the best performance. SHAP analysis showed that SiO_2 was the most important variable for reservoir temperature prediction [22,23]. Its concentration was positively correlated with reservoir temperature. The interpretability analysis also showed that the decision mechanism of the NGB model was highly consistent with domain knowledge in geothermal studies. This supported the reliability of the model for reservoir temperature estimation.

Haffou et al. [22] used 99 hydrogeochemical samples and reservoir temperature records from northern Morocco. They developed five machine learning models, including DTR, XGBoost, XRT, NGB, and DNN. XGBoost performed the best. SHAP analysis again confirmed that SiO_2 was the core variable in reservoir temperature prediction. Based on the predicted reservoir temperatures, the authors combined the volumetric method with Monte Carlo simulation to evaluate geothermal power generation potential in the study area. Their results further confirmed the strong potential of machine learning for geothermal reservoir temperature prediction and exploration.

Zhang et al. [24] used hydrogeochemical and depth data from 160 wells in the southern Songliao Basin. They combined the ALO algorithm with five machine learning models and developed reservoir temperature prediction models. The ALO-GPR model achieved the highest accuracy. Reservoir depth, total sodium plus potassium concentration, and boron content were the three most important predictors. SHAP analysis quantified the contribution and influence of each input feature on temperature prediction.

4.2. Thermophysical Property and Parameter Inversion

For reservoir thermophysical property prediction, Zheng et al. [25] addressed the limitations of the traditional thermal pulse method. In conventional testing, the theoretical model is highly idealized, fitting errors are often large, and the test process is time-consuming. They proposed a machine-learning-based inverse analysis method for rock and soil thermal properties. They first used Monte Carlo numerical simulation to build a temperature response curve (TRC) dataset. This dataset covered different rock and soil types as well as different water and ice contents. They then compared BP, CNN, and SVR for inversion performance. The final model used the first 50 s of TRC data from a heating probe together with a BP algorithm. It achieved simultaneous, rapid, and highly accurate estimation of thermal conductivity and specific heat capacity. The MAPE for specific heat capacity was as low as 0.3%, and the MAPE for thermal conductivity was as low as 0.87%. These results were much better than those of traditional theoretical methods.

For reservoir parameter inversion, Suzuki et al. [26] proposed an automated machine learning method for estimating input parameters in geothermal reservoir modeling. They generated a large training dataset using the TOUGH2 simulator. After comparing several algorithms, they selected LightGBM as the final model. The method achieved simultaneous estimation of permeability distribution and source-sink conditions. It was validated in 2D and 3D simulation cases as well as in an actual field-scale model. While maintaining high accuracy, it improved computational efficiency by one to two orders of magnitude. The authors designed a two-stage machine learning framework. Model 1 estimated source-sink conditions from temperature and pressure distributions through classification and regression. Model 2 then estimated permeability distribution using both source-sink conditions and temperature–pressure distributions. In the 3D problem, LightGBM reached 1.0 in accuracy, F1-score, and MCC for source-sink location classification. The R^2 values for source-sink enthalpy and flow rate regression were 0.929 and 0.968, respectively. The R^2 for permeability distribution estimation reached 0.868. To incorporate physical principles directly into the mathematical inversion, Ishitsuka and Lin [27] developed a physics-informed neural network framework for natural-state hydrothermal systems. By embedding mass and energy conservation equations directly into the neural network loss function, their model successfully predicted the spatial distributions of subsurface temperature, pressure, and permeability from sparse well observations, ensuring that the purely data-driven predictions remained consistent with underlying geothermal principles. Addressing multi-source data integration in enhanced geothermal systems, Chen et al. [28] established a deep learning-based joint inversion framework that assimilates both hydrogeological and geophysical observation data. This approach combined a convolutional variational autoencoder with an ensemble smoother under multiple data assimilation to characterize complex, non-Gaussian fracture aperture fields, thereby significantly reducing parameter uncertainty and enhancing the reliability of long-term thermal performance predictions.

4.3. Production–Reinjection Optimization and System Scheduling

Wang et al. [29] addressed the optimization of geothermal production–reinjection schemes. They proposed a machine-learning-based optimization method. By building a surrogate model, they achieved rapid optimization of production and reinjection parameters. This improved both development efficiency and economic performance. The method also provided a new technical pathway for designing geothermal production–reinjection schemes.

For integrated energy systems with ground source heat pumps, related studies have also developed machine-learning-based energy scheduling optimization methods. These methods can coordinate multiple energy sources and improve dispatch efficiency. They further extend the application scope of machine learning in GSHP system optimization.

4.4. Summary and Current Limitations in Reservoir Characterization

To compare different technical routes more clearly, Figure 5 summarizes typical studies on geothermal reservoir parameter prediction. It includes simulation-driven dataset construction, machine-learning-based inversion workflows, method framework comparisons, and typical results on model performance and interpretability [30]. Figure 5 shows that current reservoir characterization studies are no longer limited to single-parameter regression. They are gradually forming a complete technical chain that includes simulated sample generation, surrogate prediction, and feature interpretation. Methods such as SHAP have also improved the interpretability of model outputs.

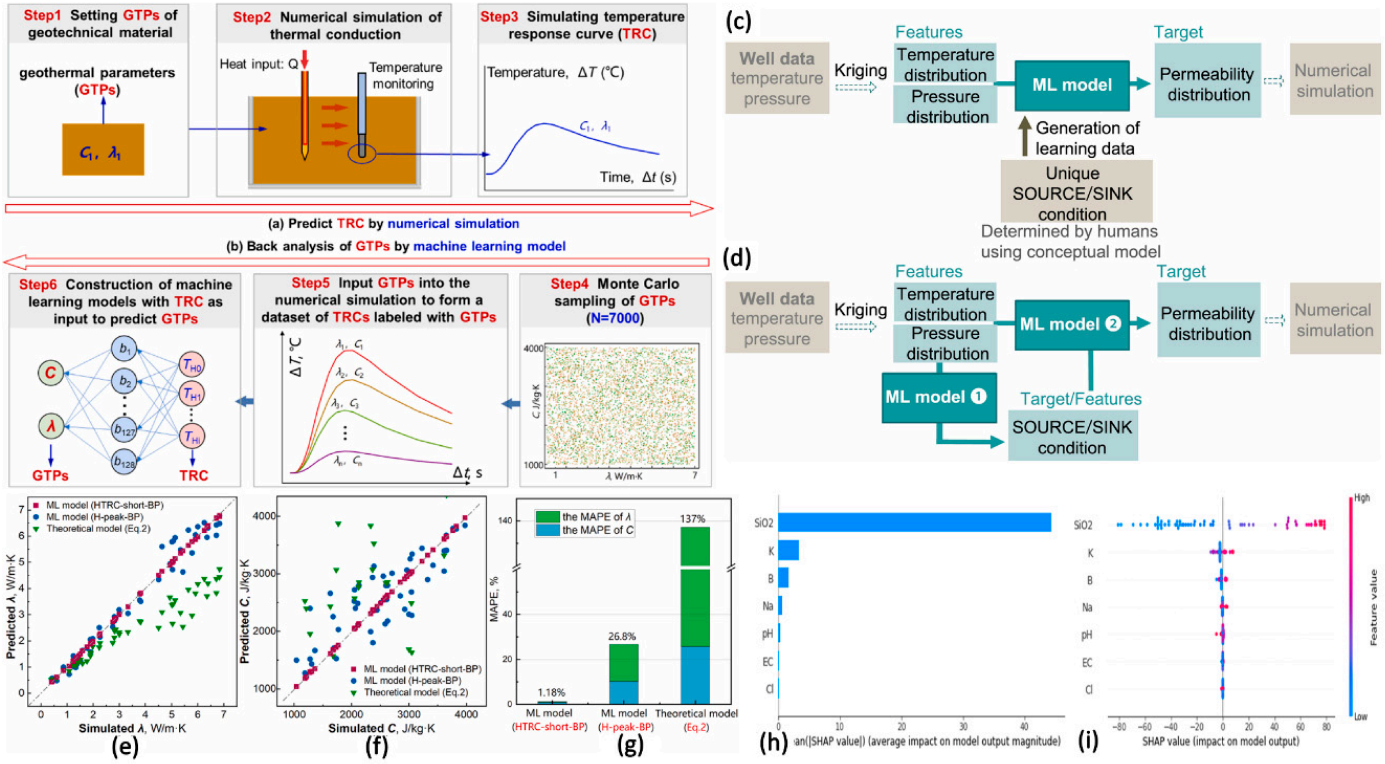


Figure 5. (**a**,**b**) Numerical simulation, Monte Carlo sampling, TRC dataset construction, and machine-learning-based geothermal parameter inversion by Zheng et al. [25]. (**c**,**d**) Method framework comparison by Suzuki et al. [26]. (**e**–**g**) Performance comparison between machine learning models and theoretical methods [25]. (**h**,**i**) Global feature influence on reservoir temperature prediction using NGB [21].

Current machine learning applications in reservoir characterization and parameter prediction still have several limitations. Most studies rely on numerical simulation data or small experimental datasets. Current studies often ignore scale effects in reservoir characterization. Machine learning models trained on laboratory-scale data face major challenges. These models do not easily transfer to field-scale geothermal systems. Laboratory core samples only represent a very small physical volume. Real geothermal reservoirs contain large-scale fracture networks and strong spatial heterogeneity. Therefore, researchers must define an appropriate representative volume element (RVE). An accurate RVE bridges the gap between micro-scale laboratory physics and macro-scale engineering. Future studies must explicitly address these spatial upscaling issues. This crucial step will ensure the reliability of field-scale parameter inversion. In addition, the data often come from a single geothermal area. The learned patterns may therefore contain strong regional characteristics. When evaluating such results, researchers should not focus only on R^2 or RMSE. They should also consider sample size, data distribution, validation strategy, and external testing.

Model generalization remains insufficient. Model interpretability is also still inadequate for engineering use [21,25,26]. For example, the dataset used by Ibrahim et al. [21] included only 84 samples. This limited the generalization ability of the model and could not support training of more complex models. The dataset used by Zhang et al. [24] came only from the southern Songliao Basin. It had a limited sample size, and the model still needs validation under other geological settings. Beyond reservoir temperature, important targets also include thermal conductivity, specific heat capacity, geothermal gradient, shallow rock and soil thermal properties, and regional thermal parameter distributions [31,32]. Machine learning has already been used for inverse analysis of thermal pulse experiments, parameter estimation from borehole thermal response tests, and rapid regional thermal parameter mapping. These applications show promising potential [33,34]. Overall, the research foundation in this field is relatively mature. However, future work should move away from simple algorithm stacking. More attention should be given to data quality improvement, external validation, cross-site transfer, and integration with physical constraints.

5. Machine Learning for Geothermal System Development and Operational Optimization

Development and operational optimization are critical for improving geothermal efficiency and reducing cost. These tasks include drilling optimization, reservoir production optimization, and well control optimization. As geothermal development moves from resource identification to refined operational management, the role of machine learning is also expanding. It is no longer limited to parameter prediction. It is becoming a tool for decision support. Traditional optimization methods rely heavily on numerical simulation. They often suffer from high computational cost and slow convergence. Machine learning can greatly improve optimization efficiency by building surrogate models.

In geothermal development and operational optimization, high-fidelity numerical simulations are an indispensable prerequisite for generating the robust, physics-grounded datasets required to train machine learning surrogate models. Before data-driven algorithms can efficiently optimize well controls or production strategies, they must learn from complex multiphysics scenarios. For example, foundational simulation studies by Han et al. [35] and Gao et al. [36] utilized discrete fracture network models to capture the effects of heterogeneous apertures, flow channeling, and various injection parameters on long-term heat extraction performance. In the context of intelligent geothermal development, these comprehensive numerical studies function primarily as essential data generators. They produce the high-dimensional, physically consistent datasets needed to train accurate surrogate models, thereby bridging the gap between fundamental thermo-hydro-mechanical mechanisms and advanced machine-learning-based decision support.

For drilling optimization, Zhai et al. [37] used drilling diagnostic data from well 58–32 at the U.S. FORGE site. They built two shallow machine learning models, BPNN and RF, for drilling depth prediction. The RF model required only 4.981 s for training and achieved an R^2 of 0.9995 on the test set. Compared with BPNN, it improved computational efficiency by 91.82% and prediction accuracy by 1.04%. This result demonstrated the effectiveness of shallow machine learning for large geothermal drilling datasets. The authors removed outliers from 379,828 measured drilling records, analyzed feature correlations, and applied Min–Max normalization. They selected core input features based on RF feature importance. They then built BPNN and RF models, optimized hyperparameters with a control-variable approach, and split the data into training and testing sets at a ratio of 7:3. Combined with K-fold cross-validation, they evaluated the models using R^2, RMSE, and MAE. The results showed that random forest clearly outperformed BPNN on this large-scale dataset.

Khaled et al. [38] focused on real-time prediction of bottom-hole circulating temperature (BHCT) in high-temperature geothermal drilling. Traditional numerical models have low computational efficiency for this task. The authors developed an LSTM-based BHCT real-time prediction model. They first used a thermo-hydraulic coupled model validated with field data from Utah FORGE to generate a dataset with 132,000 data points. Among six tested machine learning models, LSTM performed the best under all test conditions. Its MAE was lower than 1.5 °C and its RMSE was lower than 4.5 °C. It could complete BHCT prediction at the millisecond scale, which meets the demand for real-time field decision-making [38,39]. This study showed that LSTM can capture transient BHCT behavior under both static and dynamic drilling conditions. It therefore provides technical support for active temperature management during geothermal drilling.

For reservoir production optimization, Chen et al. [40] addressed the bottleneck of computationally intensive simulation and slow convergence in multi-objective optimization of EGSs. They proposed an active-learning-enhanced evolutionary multi-objective optimization algorithm, ALEMO. This method was coupled with hydrothermal simulation in fractured media to achieve efficient multi-objective design. It required only 500 simulation runs to produce optimization results better than those of NSGAII and MOEAD after 5000 runs. The computational efficiency improved by 10 to 100 times [40]. The method introduced a probabilistic neural network to predict Pareto dominance relationships. It also combined active learning with hypervolume-driven attentive subspace search. Benchmark tests and engineering cases showed that the number of numerical simulations could be reduced by one to two orders of magnitude.

Wang et al. [41] addressed geothermal reservoir development optimization under uncertain permeability. They proposed a closed-loop optimization framework based on a deep learning surrogate model. They built a hybrid CNN-LSTM surrogate model, combined it with IES for reservoir parameter data assimilation, and then used a differential evolution algorithm for production optimization. This framework can support efficient real-time optimization and data assimilation in geothermal reservoirs. It can also improve economic performance while reducing uncertainty in reservoir parameters [41,42]. The CNN-LSTM model extracted spatial information from the permeability field and mapped it to production dynamics. The framework alternated between data assimilation and production optimization. In this way, it achieved real-time well control optimization together with dynamic reservoir parameter estimation [43].

Figure 6 presents several representative machine learning applications in geothermal development optimization. These include a surrogate-model-driven multi-objective optimization framework, a drilling data modeling workflow, and random-forest-based drilling depth prediction. Figure 6 shows two main advantages of machine learning in this area. First, surrogate models can replace high-cost numerical simulations. Second, field data can support rapid prediction and decision-making.

For EGS development optimization [40,41], Zhao et al. [44] combined thermo-hydro-mechanical numerical simulation with machine learning and established a multi-objective optimization framework for EGS heat extraction. They built an NRBO-BP neural network model to predict multiple performance indicators at the same time [45]. They then combined MOSOA with entropy-weighted TOPSIS to optimize engineering parameters. After optimization, the system life was extended by more than 10 years, the injection–production pressure difference decreased by 76.4%, and both heat extraction efficiency and system stability improved significantly. The authors built a THM-coupled finite-element model in COMSOL (https://www.comsol.com/, accessed on 1 July 2026), analyzed the effects of engineering parameters on heat extraction performance, developed the NRBO-BP neural network, and finally used it as a surrogate model for multi-objective optimization.

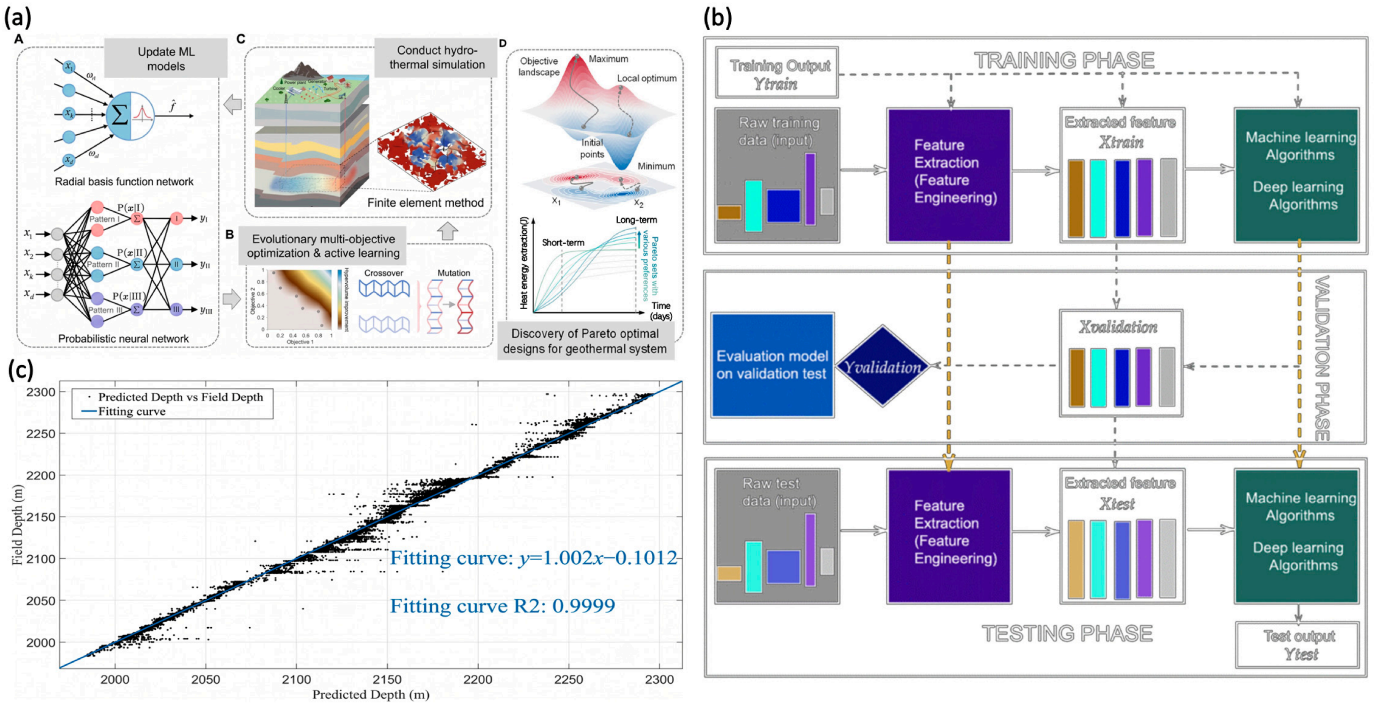


Figure 6. (**a**) Overall framework by Chen et al. [40]: surrogate model updating, evolutionary multi-objective optimization, thermo-hydro-mechanical numerical simulation, and Pareto-optimal solution discovery. (**b**) Workflow of the machine learning algorithm [37]. (**c**) Comparison between measured depth and depth predicted by the random forest regressor [37].

Yan et al. [46] addressed the high computational cost and low optimization efficiency in EGS reservoir management. They developed a general physics-informed machine learning framework. They built a forward surrogate model based on a Fourier neural operator (FNO). The relative error of the surrogate model was as low as 1.27 ± 0.89%, and the prediction speed was 4564 times faster than that of the numerical simulator. They also designed two optimization schemes. One used a control network for end-to-end mapping. The other used a deep learning optimizer for direct solution. Both schemes achieved efficient optimization of EGS heat extraction. The combination of the control network and the Adam optimizer offered the best balance between accuracy and efficiency.

At present, machine learning in geothermal development and operational optimization has mainly been validated in ideal simulation environments. This direction still has two clear weaknesses. First, most validation settings are still restricted to idealized numerical models. Real geothermal reservoirs have complex geological conditions, strong heterogeneity, multiphysics coupling, parameter drift, and observation noise. These factors are often not fully represented. Second, optimization objectives usually focus on heat extraction efficiency or outlet temperature. They rarely include long-term economics, wellbore safety, reservoir decline, or environmental risk at the same time [47]. Therefore, current studies mainly demonstrate algorithmic feasibility. There is still a clear distance between these studies and actual engineering deployment.

6. Machine Learning for Heat Transfer Performance Prediction and Control of Geothermal Systems

Heat transfer performance prediction and control are key to improving geothermal utilization efficiency. These tasks include performance prediction of borehole heat exchangers and control of ground source heat pump systems. Traditional methods rely on numerical simulation or analytical models [2,48]. They often have low computational efficiency or

limited accuracy. Machine learning can model operational data directly. It can therefore predict heat transfer performance quickly and accurately, and it can also support system optimization and control.

6.1. Component-Level Performance Prediction

For borehole heat exchanger performance prediction, machine learning has been used for outlet temperature prediction, key thermal parameter estimation, and rapid assessment of regional shallow geothermal potential [49]. Existing studies show that when input variables are relatively clear, models such as XGBoost, random forest, and support vector regression can usually achieve high prediction accuracy [50,51]. Feature contribution analysis can also help identify the main influencing factors.

Taşdelen et al. [52] focused on the prediction of outlet air temperature in ground–air heat exchangers (GAHE), which is a key demand in system design. They used CFD simulations to generate 354 sets of GAHE operational data. They then built five machine learning models: XGBoost, random forest, decision tree, support vector regression, and K-nearest neighbors. XGBoost performed the best. SHAP analysis showed that inlet air temperature, ground temperature, and Reynolds number were the key factors controlling GAHE performance. This study also quantified the contribution of each parameter and provided a highly accurate machine learning method for design optimization and performance prediction of geothermal heat exchangers.

Bourhis et al. [53] addressed the high cost and long duration of thermal response tests (TRTs), which limit rapid regional-scale evaluation of geothermal potential. Based on measured TRT data from 174 boreholes in west-central Switzerland, they developed XGBoost models to predict key geothermal parameters at both site and regional scales. At the site scale, the MAE values for undisturbed ground temperature, effective thermal conductivity, and borehole thermal resistance were as low as 0.655 °C, 0.194 W/(m·K), and 0.0164 m·K/W, respectively. These errors were close to the uncertainty level of field TRT measurements. The authors then used the best model to generate spatial distribution maps of geothermal parameters. They also compared the results with official geological models. This work enabled rapid screening of regional shallow geothermal potential.

6.2. System Control and Operational Optimization

For the control and optimization of ground source heat pump (GSHP) systems [54], real-time coefficient of performance (COP) calculation is often hindered by redundant model inputs. To address this, Zhang et al. [55] conducted a case study on a GSHP system in a Tianjin office building. They initially collected 10 operational parameters and applied LASSO and correlation analysis for rigorous feature selection [56–58]. By screening out the most informative features, they reduced the input requirement to only four to six parameters while maintaining high predictive accuracy. Subsequently, they developed ELM, BPNN, and SVM models to predict the COP of both the heat pump unit and the entire system. Their results demonstrated that the ELM model outperformed the others in both accuracy and computational efficiency, proving to be a highly efficient solution for COP prediction in GSHP systems.

Furthermore, Wang et al. [59] noted that while most optimization studies focus on the design stage of GSHP systems, fewer address the operational strategies of systems already in service. To bridge this gap, they proposed a novel optimization framework for existing GSHP systems using a machine learning surrogate model. The authors first reproduced the real-world operation of a GSHP system using a closed-loop numerical model and generated a training dataset via Latin hypercube sampling. To overcome the computational burden, they replaced the numerical model with an XGBoost surrogate, which achieved remarkable

accuracy: the absolute error for temperature prediction was below 0.1 K, and the absolute percentage error for heat extraction was under 2.0%. To accommodate a variable number of input parameters, a process decomposition method was introduced. Finally, by applying a multi-objective bald eagle search optimizer [60], they optimized both regular and irregular operating modes. This optimized strategy successfully reduced the daily operating time by 2% to 9% and saved 0.6 to 6.0 kWh of electricity per day.

6.3. Regional Shallow Geothermal Potential Assessment

For regional shallow geothermal potential assessment, Previati et al. [61] pointed out that many regional studies ignore the effect of groundwater-flow-driven convective heat transfer. They also noted that direct numerical simulation is too computationally expensive for large-scale application. They therefore proposed a new regional-scale assessment method based on a machine learning surrogate model. They built a three-dimensional finite-element model of an infinite line heat source that considered groundwater flow and then developed an artificial neural network surrogate model. The method enabled rapid calculation of geothermal potential under groundwater flow conditions. In a 12,500 km^2 area of the Po Plain in Italy, the method was used to generate a regional geothermal potential map. The results showed that groundwater flow could increase GSHP heat exchange potential by as much as 250%. The authors also derived a pseudo-g function that included groundwater convection and combined it with the ASHRAE design method to calculate rock and soil thermal resistance and geothermal exchange potential under different conditions.

Similarly, Gao [62] evaluated the shallow geothermal potential in the urban area of Changchun. The study involved obtaining thermal property parameters through comprehensive indoor and outdoor experiments and utilizing borehole temperature measurements to define the shallow ground temperature field. By combining machine learning with ArcGIS (https://www.arcgis.com/), Gao developed spatial prediction models for soil and rock thermal conductivity, as well as ground temperature at a 100 m depth. Furthermore, a hydrothermal coupled numerical model was established for a shallow coaxial borehole geothermal system, which was then used to train RF-SVR and other surrogate models. Ultimately, these integrated methods enabled a thorough geothermal resource assessment and extraction potential prediction for the study area, concurrently analyzing the effects of multiple parameters on heat extraction performance.

6.4. Summary and Current Limitations

Figure 7 summarizes representative studies on machine learning for geothermal heat transfer performance prediction and heat pump control. It includes system modeling routes, COP prediction frameworks, regional potential assessment results, and SHAP-based feature contribution analysis. Overall, Figure 7 shows that this research direction has expanded from single performance prediction to operational strategy optimization and regional resource assessment. It also highlights the scalability of machine learning from the component level to the system level and then to the regional level.

Machine learning has already shown high efficiency in heat transfer performance prediction and control. However, most studies focus on one specific system or one specific region. The resulting models are often difficult to transfer across climate zones or across different types of geothermal utilization systems. In addition, most current studies focus on short-term performance prediction. Few consider long-term problems such as thermal imbalance or performance degradation during continuous operation. This limits the value of these models for long-term optimization and prevents them from supporting full life-cycle operation of geothermal systems [63].

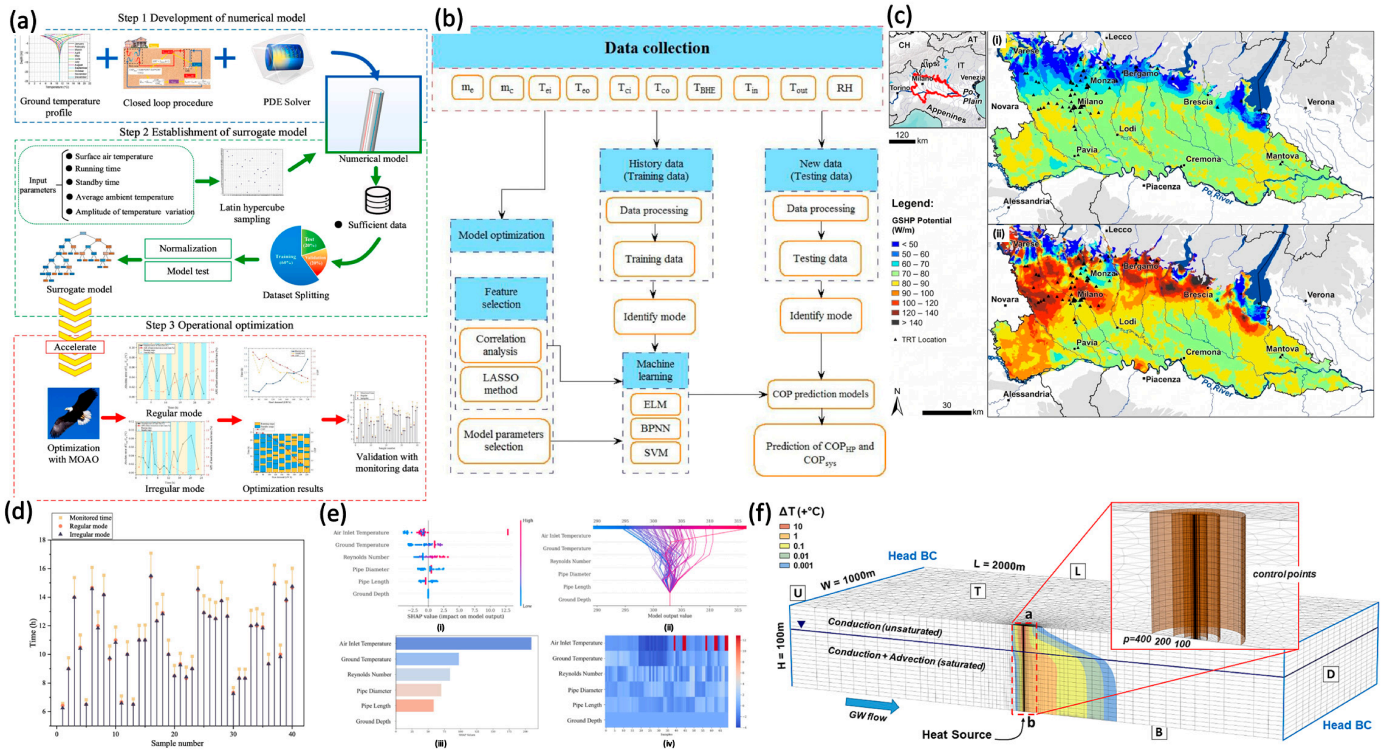


Figure 7. (**a**) Technical route by Wang et al. [59]. (**b**) Framework of the COP prediction model developed by Zhang et al. [55]. (**c**) Regional comparison between conductive potential and groundwater-convection-affected potential by Previati et al. [61]. (**i**) and the potential considering the advective heat transport (**ii**). The location of public available thermal response tests (TRT) is shown by black triangles. (**d**) Optimization results for 40 representative days, including actual operation, optimized regular mode, and optimized irregular mode [59]. (**e**) SHAP-based feature analysis using the XGB model: (**i**) SHAP summary plot, (**ii**) SHAP stream plot, (**iii**) feature significance evaluation, and (**iv**) SHAP heatmap [52]. (**f**) Configuration of the three-dimensional FEM model used to evaluate radial temperature disturbance of the line heat source [61]. In subfigure (**f**), labels denote the model boundary faces: U = upstream, T = top, B = bottom, and D = downstream. L = lateral, 'a' and 'b' indicate the specific nodes defining the linear heat source.

7. Physics-Informed Machine Learning and Operator Learning in Geothermal Energy

Purely data-driven machine learning models often suffer from weak generalization and poor physical consistency. Physics-informed machine learning (PIML) refers to methods that explicitly embed governing equations, conservation laws, or boundary conditions into the model architecture or loss function. These methods aim to preserve fast prediction while satisfying strict physical constraints. To contextualize this development within the broader renewable energy landscape, a recent comprehensive review by Parsa [64] highlights that while sectors like wind energy are currently in the spotlight for PIML applications, its adoption in geothermal, solar, and biomass systems remains in an infant stage. Nevertheless, this early-stage cross-disciplinary integration offers a transformative pathway for geothermal engineering. By explicitly embedding physical conservation laws, PIML can effectively address the limitations of purely data-driven approaches [65]. Alongside typical PIML methods like physics-informed neural networks (PINNs), neural operators such as the Fourier neural operator (FNO) have emerged. However, it is important to note that the term "physics-informed" is sometimes used too broadly in the literature. An FNO trained solely on datasets generated by numerical simulators learns the nonlinear mapping between infinite-dimensional parameter spaces and solution spaces. While it

captures the underlying physical behavior implicitly from high-fidelity data, it remains fundamentally a data-driven surrogate model unless physical laws are explicitly integrated into its training process.

In the domain of operator learning, Yan et al. [46] addressed the high computational cost and low optimization efficiency in enhanced geothermal system (EGS) reservoir management. They developed a comprehensive machine learning framework and built a forward surrogate model based on an FNO. By training on 4141 simulation samples generated via Latin hypercube sampling from a thermo-hydraulic coupled model, the FNO learned the mapping between reservoir parameters and both the temperature field and production temperature. The relative error of the surrogate model was as low as $1.27 \pm 0.89\%$, and the prediction speed was 4564 times faster than that of the numerical simulator. They also designed two optimization schemes—one using a control network for end-to-end mapping and the other using a deep learning optimizer—both of which efficiently optimized EGS heat extraction [46,66].

Similarly, Shi et al. [67] focused on fractured geothermal reservoirs, where numerical simulation is usually complex and time-consuming. They proposed a dataset construction framework and an FNO-based prediction model to account for the dynamic coupling between fracture morphology and injection–production parameters. By generating a multi-scenario dataset through 1100 numerical simulations of random fracture networks, they established a model for predicting the temporal evolution of the temperature field. The FNO model significantly outperformed conventional CNN models, achieving high accuracy with only 8641 trainable parameters and completing single-sample inference within one minute. To improve generalization, the authors applied max-pooling downsampling, fixed-interval sampling, and circular shift data augmentation, along with a hierarchical temporal aggregation strategy for long-horizon iterative prediction.

As shown in Figure 8, physics-informed machine learning in geothermal energy has begun to form a complete framework. It covers forward surrogate modeling and optimization-control solutions. It includes both temperature field prediction in fractured reservoirs and control network design for EGS management. Figure 8 further shows that, compared with traditional purely data-driven models, PIML places more emphasis on embedding physical constraints and solving long-sequence, multiphysics-coupled problems.

Physics-informed machine learning offers a new way to address the generalization problem of purely data-driven models. Physics-informed methods like PINNs and FNOs show great promise. However, current studies lack a critical assessment of their limitations. First, these models struggle with uncertainty quantification. They often fail to evaluate the high uncertainty in subsurface data. Second, modeling complex fracture heterogeneity remains very difficult. The embedded physical constraints often oversimplify real geological structures. Third, these surrogate models have poor extrapolation capabilities. They may fail easily under new operational conditions outside their training distribution. Fourth, the computational cost of training these hybrid models is extremely high. Solving complex physical equations during the training process requires massive computing power. Finally, scaling these models to field-scale systems is a major barrier. Most current validations only use small-scale or simplified simulations. Researchers must solve these fundamental problems before practical field deployment.

Before concluding, it is crucial to recognize that the applicability of the aforementioned machine learning methods is fundamentally tied to the realities of regional geothermal engineering. Two practical challenges stand out: extreme data scarcity and the need for integrated energy utilization. First, regional reservoir characterization often suffers from severely limited subsurface data. However, recent studies in the Zagreb geothermal field, Croatia, have demonstrated that even with very small initial datasets [68], reliable reservoir

characterization can be achieved by integrating spatial interpolation methods with rigorous statistical validation. This proves that proper statistical control can effectively compensate for sparse field measurements before deploying more complex data-driven models. Second, practical utilization is increasingly moving toward integrated heat and power production. For low-enthalpy resources, such as those in the Zharkent depression, Kazakhstan, maximizing thermal energy extraction requires combining binary geothermal technologies with cascading district heating networks [69]. These broader regional studies emphasize that future intelligent frameworks must be adaptable to both data-sparse environments and complex multi-generation systems.

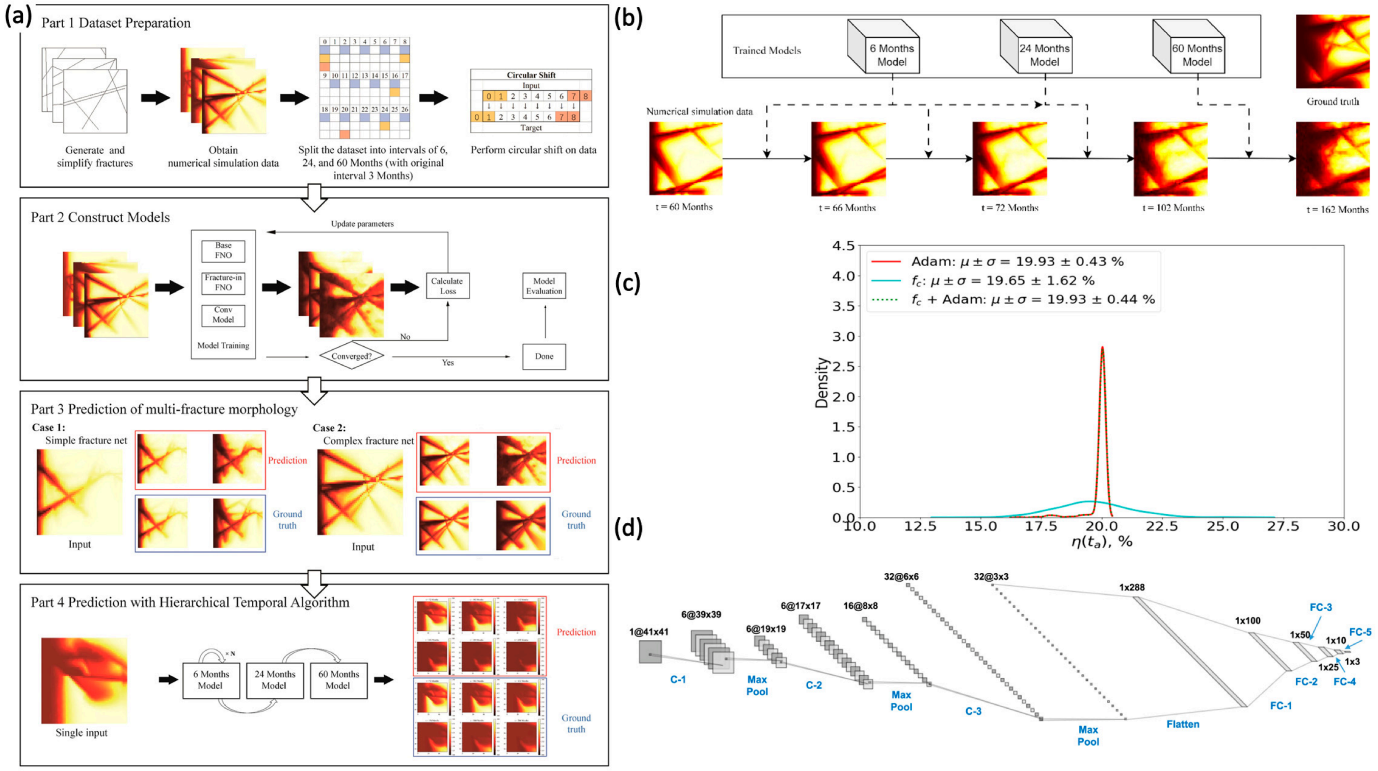


Figure 8. (**a**) Overall workflow by Shi et al. and the application of physics-informed or neural-operator methods to temperature field prediction in fractured geothermal reservoirs. (**b**) Schematic of hierarchical temporal aggregation [67]. (**c**) Distribution of optimization results under different schemes, showing that PIML is more efficient than traditional numerical-simulation-based optimization [46]. (**d**) Architecture of the control network [46].

8. Conclusions and Future Perspectives

8.1. Current State of Research

In recent years, machine learning in geothermal energy has evolved from early exploratory studies to deeper applications across multiple stages. It now covers the full workflow, from geothermal resource exploration and reservoir characterization to development and operational optimization, as well as heat transfer performance prediction and control. In terms of algorithm types, supervised learning is still the dominant approach. These methods perform well on labeled geothermal data. They have shown clear advantages over traditional methods, especially in tasks that require accurate results, such as reservoir parameter prediction and drilling optimization. In terms of publication trends, the number of related studies has increased significantly since 2021. As illustrated in Figure 9, this reflects the growing attention paid to machine learning in the geothermal field. However, the maturity of applications differs across stages. Applications in reservoir

characterization and production-operation management are relatively mature, and many studies have verified their effectiveness. In contrast, studies on exploration, drilling, and environmental control are still fewer and leave more room for further exploration. In addition, physics-informed machine learning has emerged as a new research direction. It offers a promising route to address the limited generalization of purely data-driven models and is becoming a new hotspot in this field.

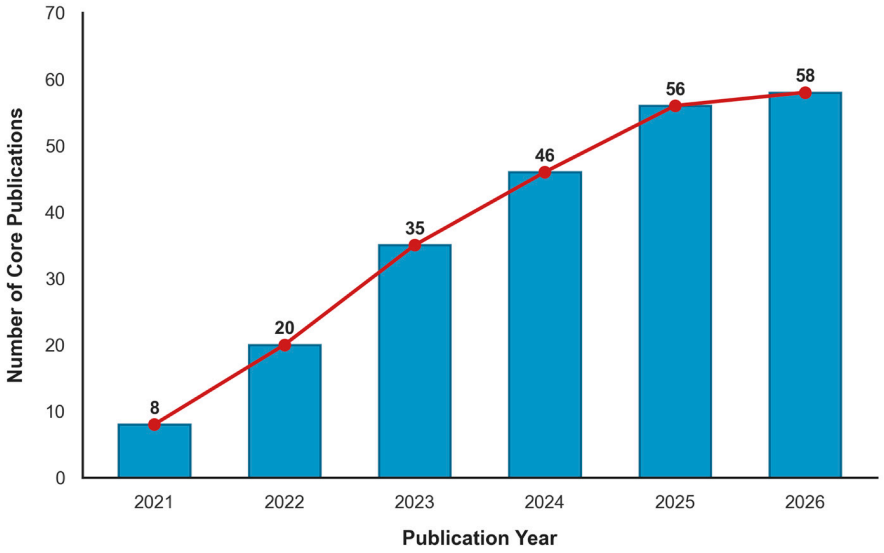


Figure 9. Annual publication trend of machine learning applications in geothermal energy (2021–2026).

8.2. Critical Comparison of Model Complexity and Applicability

The current literature shows a clear trade-off between model complexity and practical applicability. Complex algorithms like deep neural networks often achieve high accuracy on large and uniform datasets. However, these complex models are highly prone to overfitting when applied to small field-collected geothermal datasets. They also require significant computational resources and lack decision transparency.

In many geothermal tasks, simpler models actually outperform complex approaches. Tree-based algorithms like random forest and XGBoost show strong robustness against missing values and outliers in geological data. They naturally provide clear feature importance rankings. This characteristic makes them highly suitable for regional prospectivity mapping and reservoir temperature prediction. Shallow machine learning models also show distinct advantages in computational efficiency. For example, simple regression models can process massive drilling data streams in seconds. In contrast, deep networks often struggle with lengthy training times and hyperparameter tuning under similar conditions.

Therefore, algorithm selection should strictly align with data scale and specific task requirements. Deep learning architectures and neural operators are better suited for dynamic reservoir simulations and multiphysics surrogate modeling. These specific tasks can provide sufficient synthetic data to train deep networks. Conversely, simple ensemble models should remain the preferred choice for early-stage exploration and field-scale parameter inversion. Researchers must stop blindly pursuing algorithmic complexity. They should instead prioritize data quality, model interpretability, and field deployment feasibility.

8.3. Current Limitations

Machine learning has achieved meaningful progress in geothermal research. However, from the perspective of engineering application, many urgent problems still need to be solved.

(1) Limitations at the data level. High-quality labeled data are extremely scarce in the geothermal field. This is the most fundamental factor restricting machine learning applications at present. Most studies rely on numerical simulation data or small measured datasets. Their spatial coverage and diversity are clearly insufficient. As a result, model generalization is weak, and cross-scenario application is difficult. At the same time, geothermal data come from many domains, such as geology, geophysics, and geochemistry. Their heterogeneity is strong. Effective methods for data integration are still lacking, and this also limits performance improvement. Many reviewed studies rely heavily on synthetic datasets. Simulators such as TOUGH2 and COMSOL generate these datasets. This reliance introduces a significant domain gap. Actual field conditions are much more complex than ideal simulations. Therefore, simulation-based training has clear limitations. The trained models may fail in real-world engineering scenarios. Researchers must assess these limitations critically. They also need specific strategies to bridge this reality gap. For example, researchers can use transfer learning to adapt simulation models. They can also use data assimilation to combine sparse field data with large simulation datasets. Ultimately, direct field validation remains essential to ensure model reliability.

(2) Lack of model interpretability. Most machine learning models used at present are black-box models. Engineers often find it difficult to understand how decisions are made. This greatly reduces acceptance in engineering practice. In geothermal engineering, safety and reliability are critical. Poor interpretability can make engineers doubt model predictions and hesitate to use them in real projects. This limits wider adoption. Explainable AI techniques like SHAP and LIME are currently popular. However, they have clear limitations. These methods can introduce their own mathematical biases. They often only show statistical correlations instead of true physical causes. Sometimes their explanations lack physical meaning in geothermal applications. A feature might appear important mathematically but make no sense geologically. Therefore, researchers must evaluate interpretability methods critically. A trustworthy model requires more than just post hoc statistical explanations. True trustworthiness requires linking these statistical explanations directly to underlying physical mechanisms.

(3) Insufficient integration of physical mechanisms. Most purely data-driven models do not adequately consider the physical laws of geothermal systems. As a result, their predictions may violate physical principles under extreme conditions or complex geological settings. This weakens model reliability. Although physics-informed machine learning has started to address this issue, current applications are still limited. In most cases, physical laws are only added as simple constraints. Deep integration between physical mechanisms and machine learning has not yet been fully achieved.

(4) Barriers to engineering deployment. Most current studies remain at the theoretical or simulation stage. Very few have been validated in real geothermal projects. At the same time, standardized workflows and evaluation systems are still lacking. This makes it difficult to compare or promote different models and methods. As a result, machine learning has not yet been fully converted into engineering benefit. In addition, many geothermal engineers still have limited knowledge of machine learning, which further increases the difficulty of deployment.

(5) Insufficient differentiation across geothermal system types. Different geothermal systems, such as hydrothermal systems, hot dry rock systems, and shallow geothermal systems, differ greatly in geological conditions and development modes. However, most current studies do not build customized models for these differences. Instead, they often apply general machine learning models. This leads to uneven performance

across different geothermal system types and prevents full use of the strengths of machine learning.

(6) Flaws in model evaluation and validation. Many cited studies report excellent predictive performance. However, these results often hide deep flaws in model evaluation. Data leakage is a common problem. Validation protocols are often weak. Researchers frequently ignore spatial cross-validation. They also rarely perform external validation on unseen fields. Reproducibility remains very low across these studies. Furthermore, models often lack robustness under operational uncertainty. Therefore, the geothermal community needs standardized evaluation practices. Researchers must adopt strict reporting guidelines. They should openly share their code and datasets. They must also test models under high uncertainty. This standardization will ensure true model reliability.

8.4. Future Research Directions

To address the above problems, future research can move forward in the following directions and promote deeper application of machine learning in geothermal energy.

(1) Build standardized geothermal datasets. Data sharing within the industry should be strengthened. Open and standardized geothermal datasets should be established. These datasets should integrate multi-source data from different regions and different geothermal system types. This will improve both data quality and diversity. At the same time, effective data integration and preprocessing methods should be developed to address data heterogeneity. These efforts will provide high-quality support for model training and validation. Researchers need practical strategies to overcome data limitations. Transfer learning can adapt models from data-rich regions to data-poor regions. Domain adaptation can help reduce the gap between simulation data and field data. Furthermore, multi-fidelity modeling is highly recommended. It combines cheap low-resolution simulations with expensive high-resolution field data. In addition, federated learning offers a new collaborative approach. It allows different geothermal operators to train models together. It protects data privacy while significantly increasing the total sample size. Finally, researchers must use rigorous spatial validation techniques. Spatial cross-validation is essential. It prevents the overestimation of model accuracy caused by spatial autocorrelation. These advanced techniques will greatly improve model generalization in future studies.

(2) Improve model interpretability. Explainable artificial intelligence methods should be studied more deeply and applied to machine learning models in geothermal research. This will help engineers understand the decision process and logic of the models. In addition, interpretability evaluation metrics tailored to geothermal applications should be developed. A systematic evaluation framework for model interpretability is also needed to support engineering deployment.

(3) Deepen the integration of physical mechanisms and machine learning. Physics-informed machine learning should be further developed to achieve deeper integration. Complex physical processes in geothermal systems, such as multiphysics coupling and heterogeneity, should be incorporated more directly into machine learning models. This will improve both reliability and generalization. At the same time, customized physics-informed models should be developed for different geothermal system types.

(4) Promote engineering deployment. Closer collaboration with real geothermal projects is needed. More field validation studies should be carried out. Machine learning models should be applied to actual geothermal field development and operation so that their real performance can be tested. In parallel, standardized workflows and evaluation systems should be established to promote standardization and wider

adoption. Training for geothermal engineers should also be strengthened so that they can better understand and use machine learning tools.

(5) Carry out differentiated studies. Customized machine learning models and application strategies should be developed for different geothermal system types, such as hydrothermal systems, hot dry rock systems, and shallow geothermal systems. These models should fully consider the characteristics and needs of each system type. Comparative studies across different geothermal systems are also needed. Such studies can summarize experience and identify common patterns for the industry.

(6) Explore emerging technologies with cautious pragmatism. While the application of new machine learning techniques—such as large language models (LLMs) and graph neural networks—is currently speculative in the geothermal sector, their potential warrants careful exploration. For instance, LLMs could be utilized to automate the extraction of critical geological parameters from unstructured historical drilling reports and the scientific literature, whereas graph neural networks could be specifically tailored to model the spatial topology of complex subsurface fracture networks. In addition, multi-technology integration should be encouraged. One promising, albeit early-stage, direction is the coupling of machine learning with digital twin technology. Although still largely conceptual in current geothermal applications, a geothermal digital twin could theoretically assimilate real-time sensor data from production and injection wells to dynamically simulate thermal depletion and optimize operational strategies, ultimately paving the way for the truly digital and intelligent operation of geothermal systems. Advanced methods like digital twins and reinforcement learning show great promise. Active learning and intelligent optimization are also emerging. However, their practical deployment faces severe challenges. Real-time data assimilation remains very difficult. The continuous propagation of uncertainty can cause system failures. Furthermore, these models often ignore strict engineering safety constraints. They also frequently overlook long-term reservoir decline. Finally, pure thermal performance must align with complex economic objectives. Future research must address these specific deployment barriers. Overcoming these challenges will enable truly intelligent geothermal operations.

(7) Adopt advanced mitigation strategies for data limitations. Researchers must address data scarcity and weak generalization using advanced techniques. Transfer learning and domain adaptation can adapt models pre-trained on data-rich fields to new target sites. Multi-fidelity modeling effectively combines abundant low-cost simulations with scarce field measurements to reduce computational costs. Federated learning allows multiple institutions to collaboratively train models without sharing sensitive raw data. Finally, rigorous spatial validation techniques like block cross-validation must replace traditional random splitting. This prevents performance overestimation caused by strong spatial autocorrelation.

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declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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