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# Study on the Effects of Radiation Insulation Film and Backfill Soil on Shallow Ground Source Heat Pumps Within 5 Meters of the Surface

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**ABSTRACT**

Ground Source Heat Pumps (GSHPs) are a sustainable solution for low-energy heating and cooling, yet their performance is significantly affected by insulation materials and surrounding soil properties. This study aims to investigate the effects of radiation insulation film and backfill soil types on the thermal performance of shallow ground source heat pumps (SGSHPs) installed within 5 meters of the surface. A simulation-based, quantitative methodology was implemented using Python in Google Colab, generating 1500 synthetic data points analysed via supervised machine learning models, including SVR, XGBoost, and Random Forest. Results showed that sand-based soils and thicker insulation layers significantly improved heat transfer and efficiency, while SVR achieved the best predictive accuracy, and XGBoost outperformed others in classification tasks. The study concludes that ML models are effective in system optimisation. Recommendations include using AI tools in design phases. The findings provide theoretical insights into geothermal optimisation and practical guidance for SGSHP design, though their generalizability is limited by the absence of real-world validation data.

**Keywords:** Ground Source Heat Pump, Machine Learning, Thermal Performance, Soil Insulation, Simulation-Based Analysis.

## INTRODUCTION

Shallow Ground Source Heat Pumps (SGSHPs) are becoming a more popular and sustainable choice both in the city and in homes when it comes to heating, as well as cooling. They appear at a depth of less than 5 m and use the constant temperatures of shallow soil layers to conduct heat. This decreases the use of fossil fuels and increases energy efficiency (Gong et al. 2022). The SGSHP performance can be influenced by two factors: backfill soil type and the application of radiation insulation film over the buried pipeline (Zhang et al., 2021). The conductivity and moisture of the soil influence the heat exchange, and that is why the selection of the backfill is vital (Chen et al., 2023).

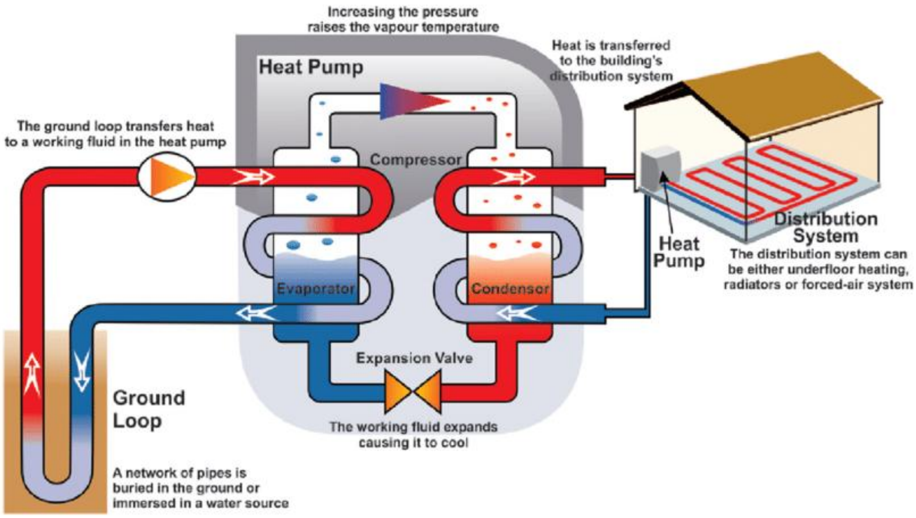


**Figure 1.** Geothermal Heat Pump Schematic

Climo et al. (2014) listed three key elements of a GHP as the ground loop, the heat pump unit and the distribution system in a building (see Figure 2). Currently, radiation-insulation films are widespread in SGSHP design, which reduces thermal losses and concentrates heat on the pipes. By regulating the ambience, the external disturbance can be reduced, and the efficiency can be enhanced (Jinxi et al. 2025). Contemporary building-simulation software can provide realistic SGSHP operation in various environments and design conditions (Christodoulides et al., 2020). Recent work uses data-driven techniques (mostly depending on ML) to capture non-linear relationships in large amounts of data to enhance the prediction (Farajollahi et al., 2024).

### Problem Statement

Although research in this area has advanced, the combined influence of insulation films and varying backfill soils in fully integrated simulation – ML studies remains insufficiently understood. Researchers tend to either isolate soil characteristics or insulation effects, and this restricts overall optimisation (Zhao et al., 2023). Many experiments focus on site-specific experiments, lowering their universal applicability across a wide range of geology and climatic conditions (Jain et al., 2023). There is also a lack of systematic simulation-based modelling with advanced ML, which can limit reliable SGSHP performance forecast (Zhang et al., 2022). There is also a loophole in classification models which determine the effectiveness of the system in various design situations. Nevertheless, such parameters are seldom considered in the SGSHPs (Lu et al., 2019). There are prediction and classification algorithms that may be used efficiently, but the purpose is to rely on a product choice of materials and backfill mixture (Sharaan et al., 2024). This study fills these gaps by using simulation data and engaging the cutting-edge ML algorithms to predict and classify the performance of SGSHP.

### Aim and Research Objectives

The research aims to investigate the influence of different radiation-insulation films, backfill soil and others on SGSHP operation performance for the 5m air layer of the ground plane.

- To build and assess classification models for determining the effectiveness of SGSHP configurations, using performance metrics.
- To develop and evaluate supervised machine learning regression models for predicting key performance indicators such as heat transfer rates, energy consumption, and system efficiency.
- To develop validated thermal and energy models to simulate the performance of the SGSHP systems in various configurations of radiation insulation films and backfill soil types.

### Significance of the Study

The results of this study would be useful to energy planners and policymakers to reduce energy consumption and improve overall system performance for HVAC engineers. The research also reinforces the convergence of green energy systems with data-driven analytics, which is consistent with the universal objectives for smart energy management.

## RELATED WORKS

This literature review presents the recent developments of SGSHP simulation, ML performance prediction, and system evaluation classification models. It establishes the theoretical foundation while highlighting critical gaps in existing knowledge.

### Simulation of Thermal and Energy Performance of SGSHPs

SGSHP performance is subject to the subsurface conditions, together with insulation and depth of installation. Simulation of SGSHP behaviour in changing geology and weather is performed with tools such as TRNSYS, COMSOL Multiphysics, and EnergyPlus. They simulate long-term system operation and soil-thermal dynamics and heat exchange (Christodoulides et al., 2020). The composition of backfills has a great impact on thermal behaviour. Different conductivities of sand, clay and gravel influence heat exchange (Ma et al., 2025). Graphite or bentonite mixtures with thermally enhanced backfills can improve conductivity and overall performance by more than 30 in comparison with traditional soil (Zhang et al., 2022). Radial heat loss is inhibited by insulation films and is of particular concern to shallow configurations where the temperature range is greater (Tian et al., 2021).

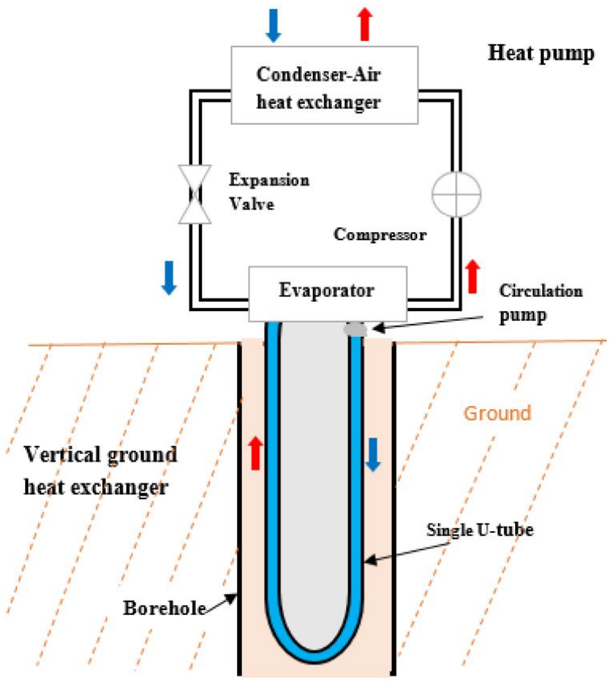


**Figure 2.** Ground Source Heat Pump System

A ground-source heat-pump system consists of a heat-pump and one or several borehole heat exchangers that exchange energy between the ground and building (Figure 2, Eswiasi and Mukhopadhyay, 2020). Some of the studies looked into the impact of insulation-film thickness and soil layers on performance. Li et al. (2024) demonstrated that a radiation film 10 mm thick could increase COP by 15% in sandy soils. Geo-environmental modelling coupled with thermal simulation provides the precise estimation of ground temperatures, which allows the design of the optimal spacing of the pipes and the backfill (Sharaan et al., 2024). Newer models have also taken into consideration real-time weather data, with simulations being strong and realistic (Zhang et al., 2021). Such deterministic models will give useful insights, but there is a small number of probabilistic or data-driven approaches that accommodate uncertainty or generalise between sites (Mao et al. 2024). The combination of simulation and ML holds a greater level of accuracy and real-time flexibility (Cho et al., 2021).

### Machine Learning Models for Predicting SGSHP Performance

ML has emerged as a strong instrument for modelling the non-linear, multi-variant SGSHP data. Typical algorithms are Random Forest, Support vector regression (SVR), and gradient boosting (XGBoost, LightGBM). Such approaches predict energy usage, the rate of heat transfer, and seasonal effectiveness (Farajollahi et al., 2024). As an illustration, there are solar collectors, a geothermal subsystem, and a poly-generation subsystem in a hybrid solar-geothermal plant (Farajollahi et al., 2024) used to capture energy. Simulation and real sensor data are used to train predictive models. Zhang et al. (2022) employed the Random Forest to forecast hourly energy consumption at a high R2. Lou et al. (2020) used SVR to evaluate performance in changing soil and insulation conditions and demonstrated climate robustness. Here, the feature selection (e.g., RFE) is used with regressors to enhance accuracy and decrease overfitting (Roka et al., 2025).

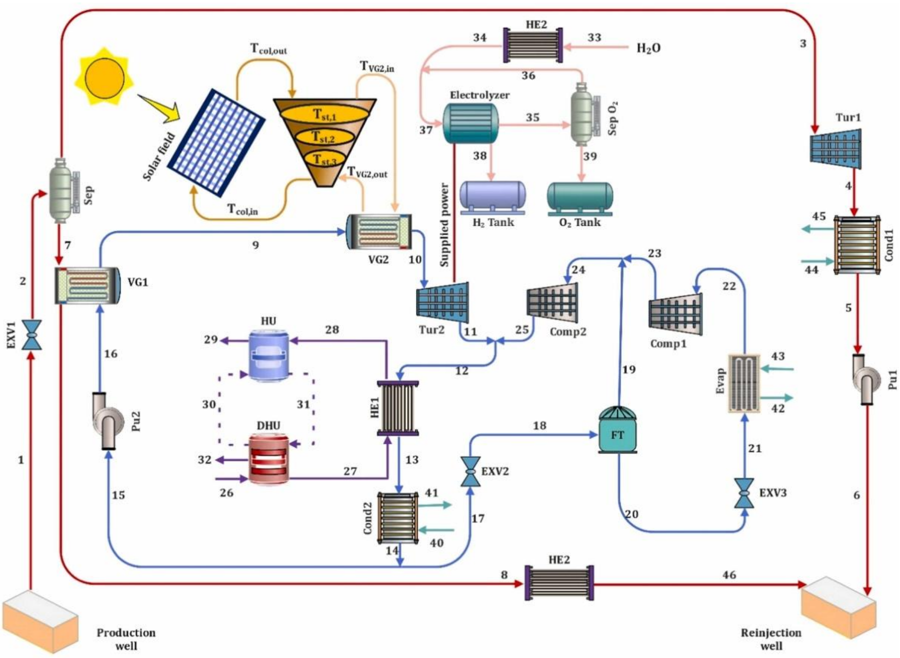


**Figure 3.** Structure of the Proposed Hybrid Power Plant

The popularity of ensemble regressors is since they show strong interactions between complex variables of the thermal, geological and environmental conditions. Gradient Boosting methods, especially XGBoost, often outperform linear models in MAE and RMSE (Zhang et al., 2020). XGBoost performed better in one comparison with the lowest MAE and highest R2 compared to XGBoost, SVR and a multi-layer perceptron (Chaoran et al., 2024). A recent movement is the integration of ML with simulation models to produce aware synthetic data to be used in training, which is useful in cases of limited empirical data (Makarakreasey, 2025). Modelled in thousands of situations, which differ in types of soil, the thickness of insulation, weather, and other factors, comprehensive datasets are obtained that increase the generalisability of models (Zuo et al., 2025).

Regardless of such improvements, there are problems. Applicability can be restricted by model interpretability, data quality and scalability. Data-intensive and computer power-oriented deep learning algorithms, such as LSTM, are not well suited to initial research (Ruhani et Porto, 2024). Researchers, therefore, prefer interpretable, ensemble-based ML that is neither complex nor performance-biased.

### Classification Models for Evaluating System Effectiveness

It is possible to categorise SGSHPs into operational conditions (effective and ineffective) to provide fast decision support. Logistic Regression, Random Forest, XGBoost, etc., are the classification models that can handle imbalanced data and do not need a balance between the result types (Lu et al., 2019). Nanjundan et al. (2022) applied the use of Logistic Regression and Decision Trees to categorise geothermal systems via performance thresholds and yielded an accuracy of 89% and a sensitivity and specificity of over 85%. Gorai et al. (2024) specified high, medium, and low efficiency categories of SGSHP simulations, and XGBoost had a high F1-score.

Classification models are assessed by using ник AUC-ROC curves and mix-up matrices. Xiong et al. (2022) discovered that the ensemble classifiers and XGBoost in particular are better, and outnumber single models proportionate to precision, recall, and log loss. According to feature-importance analyses, soil moisture and insulation conductivity were found to have a driving impact on the classification results (Ahmadi, 2025). The sensitivity and specificity are highly important to engineering; a false negative (benchmarks denoted as effective) could lead to expensive engineering errors (Cho et al., 2021).

There are a few papers associating predictive ML with classification. A two-mode workflow can give performance estimates and practical classifications, enhancing design choices (Wang et al., 2023). Such an integrated approach is adopted in this research.

### Theoretical Framework

The research is based on two theoretical frameworks, Heat-Transfer Theory and Machine-Learning Theory. Heat-Transfer Theory is used to describe physical interaction in SGSHPs. According to Fourier's Law, the rate of heat transfer relies on the thermal gradient and the conductivity of the material. This principle is critical in evaluating how different backfill soils and insulation films affect heat exchange efficiency. The theory supports simulation design and explains how environmental and material factors influence SGSHP performance. Machine Learning Theory, specifically the supervised learning paradigm, underpins the selection and implementation of regression and classification algorithms. Supervised learning uses labelled datasets to train models that predict or classify outcomes based on input features (Murphy, 2022). In the context of SGSHP, this theory justifies the use of Random Forests, XGBoost, and SVR models to predict energy performance and classify system effectiveness based on soil, insulation, and temperature variables. Together, these theories guide both the simulation modelling and data analytics aspects of the study, ensuring methodological coherence and scientific validity.

### Literature Gap

While a significant body of research exists on SGSHP systems, several gaps are evident. First, most thermal performance studies isolate variables such as soil type or insulation but rarely consider their combined effect, especially in shallow installations (<5m depth), which are more sensitive to surface conditions (Wei et al., 2020). Second, although simulation tools are well-utilised, few studies link simulation outputs with machine learning models to enhance prediction accuracy or automate design decisions (Zhang et al., 2022). Third, the majority of ML applications in this field focus on regression tasks, leaving classification modelling underexplored. This limits the ability to make binary or categorical decisions on system effectiveness, which is crucial for practical deployment (Abd-Elhady et al., 2022). Lastly, the study focuses on multifaceted model assessment based on various measures (AUC, sensitivity, specificity), and such data is frequently provided in other works (Lou et al., 2020). This data-driven, simulation-based approach that combines the heat-transfer fundamentals and supervised ML allows a holistic and data-driven approach to SGSHP design and optimisation.

## METHODOLOGY

This section describes the methodological framework to investigate how radiation-insulation film and backfill soil impact SGSHPs installed within 5 m of the surface. It discusses the method of research, research design, the simulation-based collection of data, and ML methods.

### Research Method and Research Design

The analysis is quantitative by nature and has a simulation and experimental design that integrates supervised ML algorithms to interpret SGDHP performance. The quantitative approach is preferred since it yields objective and quantifiable data on the efficiency of heat pumps and thermal exchange in various soil and insulation configurations (Weyant, 2022). Simulations can be a repeatable, scalable and isolating experimental proxy, which can be used to test variables that are expensive or otherwise impossible to test experiment-wise (Mahmoud et al., 2024). The adopted methodology is a simulated, modelled, and evaluated workflow. Modelling tools such as TRNSYS, EnergyPlus, and COMSOL Multiphysics are applied to simulate the various SGSHP configurations. These tools reproduce the thermal exchanges of soil, such as insulation and heat exchange (Gasmi et al., 2024; Barandier et al., 2024). The simulation results are employed to train and evaluate ML.

One of the comparative modelling strategies is the comparison of various backfill materials (sand, clay, gravel) and insulation film thickness at uniform operating conditions. This method elucidates the individual and combined action of the two important variables, enhancing internal validity (Mao et al., 2024). The limitation of site-specific measurements and environmental variability is lessened by using simulation data (Shin and Cho, 2021). The hybrid simulation–ML approach yields depth and generalizability (Wang et al., 2023).

### Data Collection

Simulation-based data collection produces high-fidelity synthetic data using dynamically built energy software. The variables are the type of soil, the properties of insulation films, the depth of installation (05 m), and the environmental conditions of the seasonal ground temperature (Gong et al., 2022). TRNSYS and COMSOL Multiphysics enable multiphysics modelling of SGSHP systems under diverse configurations (Mahmoud et al., 2024; Zhang et al., 2022). They forecast such performance parameters as the rate of heat transfer (W/m), the energy consumption (kWh), the temperature differences, and the coefficient of performance. The film parameters of the thermal conductivity, thickness, and emissivity are varied in different runs (Jinxi et al., 2025). Thermal properties are obtained through literature-based values to define backfill materials, including conductivity, moisture content, and specific heat capacity (Ma et al., 2025; Sah et al., 2023). The resultant data will feature continuous values to use in a regression analysis and discrete values to use in a classification analysis.

Simulation results are then outputted as CSV and then processed using Python packages such as NumPy and Pandas. The data is divided into training, validation and testing samples. This approach scales up data generation without compromising on the ecological validity and control of the experiment (Makarakreasey, 2025). It is also not affected by the uncertainty of incomplete field data or measurement noise, typical of geothermal investigations (Zuo et al., 2025). The use of synthetic datasets is an established trend in renewable-energy studies in modelling long-term operations on a short-term basis (Ruhani et al., 2024).

### Data Analysis Method

There are two components of data analysis, namely prediction and classification. Regarding prediction, the supervised ML algorithms (Random Forest Regressor, XGBoost Regressor, and Support Vector Regressor (SVR)) predict continuous values (energy consumption, rate of heat transfer, and system efficiency). MSE, RMSE and MAE are used to assess the models. Supervised models that are used in classification, such as the Logistic Regression, Random Forest Classifier, and XGBoost Classifier, are used to classify system configurations as either effective or ineffective. Evaluation measures are accuracy, precision, recall, F1 score, AUCROC, sensitivity, specificity and average log loss. All analyses were conducted in Python on Google Colab, with training, tuning, visualisation, and evaluation using Scikit learn, XGBoost, Matplotlib and Seaborn.

### Ethical Considerations

Despite the fact that this research does not entail human subjects, ethical research behaviour is maintained. All of the simulation data are produced using legally licensed software, and all the tools (TRNSYS, Google Colab, Python) are open source or referenced appropriately. The study is guided by the principles of transparency, reproducibility and intellectual honesty in the sense that datasets, code, and processes are well documented and provable. There is no conflict of interest or privacy issues. All the works are cited properly, giving credit where due.

## RESULTS AND DISCUSSION

This chapter logically decomposes the simulation-based dataset that was produced to identify the impact of the radiation-insulation films and backfill soil types on the thermal and energy performance of SGSHPs. The analysis is divided into five parts, which are data simulation, data preprocessing, descriptive statistics, regression-based prediction, and classification-based assessment. Each step is interpreted with the help of visualisation and tables that illuminate system behaviour and model performance.

### Data Simulation

In the initial step, 1,500 simulated observations were created, and each of the observations corresponded to a different SGSHP configuration. The input variables were soil type (sand, clay, gravel), insulation thickness (0-20mm), the depth of installation (0.5-5.0m), and ground temperature (8-18). Based on such characteristics, the output variables, which include the rate of heat transfer, energy consumption and efficiency of the system, were determined based on logical relationships which emulate real-world behaviour. The results were consistent with theoretical expectations: greater insulation thickness and more conductive soils (such as sand) facilitated higher rates of heat transfer. The efficiency of the system was defined as the rate of heat transfer/energy consumption, and noise was added to model natural variability. A dichotomous label was given as effective (1) when efficiency was greater than 0.28, and ineffective (0) otherwise.

**Table 1.** Sample of Simulated Dataset

| Soil Type | Insulation Thickness (mm) | Depth (m) | Ground Temp (°C) | Heat Transfer Rate | Energy Consumption | System Efficiency | Performance Label |
|---|---|---|---|---|---|---|---|
| Gravel | 1.83 | 2.72 | 12.42 | 26.29 | 81.38 | 0.33 | 1 |
| Sand | 18.35 | 3.10 | 11.34 | 32.32 | 76.11 | 0.41 | 1 |
| Gravel | 2.74 | 4.40 | 11.95 | 22.70 | 86.86 | 0.26 | 0 |
| Gravel | 19.00 | 4.91 | 13.30 | 32.03 | 78.47 | 0.39 | 1 |
| Sand | 8.92 | 2.33 | 9.61 | 32.49 | 76.28 | 0.47 | 1 |

### Data Preprocessing

Before conducting advanced analysis, the categorical soil type variable was encoded numerically to enable processing by machine learning algorithms. Four key features were retained for modelling: soil type (encoded), insulation thickness, depth, and ground temperature. These features were scaled using standardisation to normalise their ranges. The dataset was then divided into training and testing subsets (80% and 20%, respectively) for both regression and classification tasks.

### Descriptive Statistics

Descriptive statistics offered a foundational understanding of the distribution and relationships between variables. Table 2 presents the summary statistics of key variables.

**Table 2.** Descriptive Statistics of Main Variables

| Metric | Insulation Thickness | Depth | Ground Temp | Heat Transfer Rate | Energy Consumption | System Efficiency |
|---|---|---|---|---|---|---|
| Mean | 10.08 | 2.73 | 12.94 | 30.80 | 78.42 | 0.40 |
| Standard Dev. | 5.81 | 1.30 | 2.86 | 4.49 | 3.50 | 0.08 |
| Minimum | 0.03 | 0.50 | 8.00 | 17.46 | 66.97 | 0.18 |
| 25th Percentile | 4.99 | 1.61 | 10.50 | 27.70 | 76.04 | 0.34 |
| Median | 10.25 | 2.72 | 12.84 | 30.83 | 78.36 | 0.40 |
| 75th Percentile | 15.11 | 3.88 | 15.37 | 34.01 | 80.89 | 0.45 |
| Maximum | 19.99 | 5.00 | 17.99 | 43.18 | 89.10 | 0.64 |

Box plots further revealed how these variables varied by soil type. Figures 1–5 illustrate these distributions. Notably, insulation thickness (Figure 1) was uniformly distributed across all soil types, indicating random allocation during simulation. Depth distributions (Figure 2) were consistent across soil types, ensuring fair comparison.

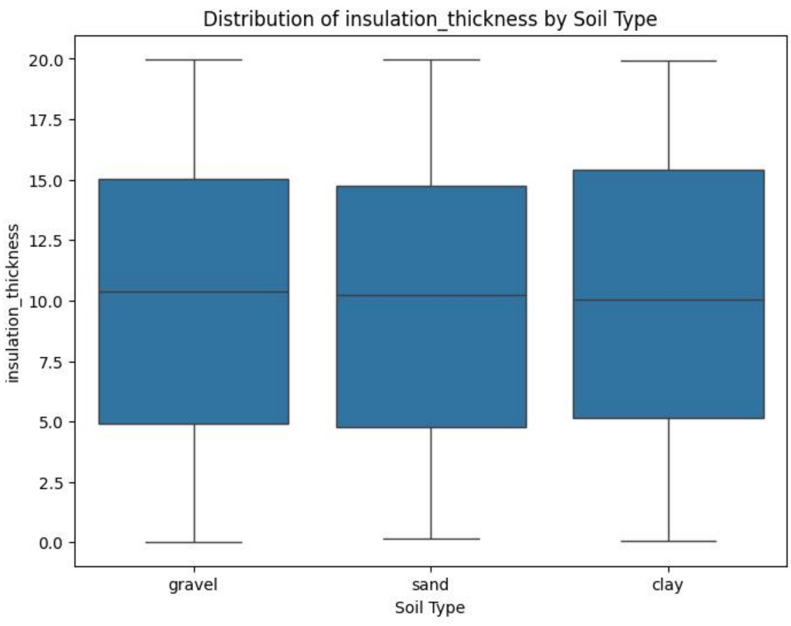


**Figure 4.** Distribution of Insulation Thickness by Soil Type

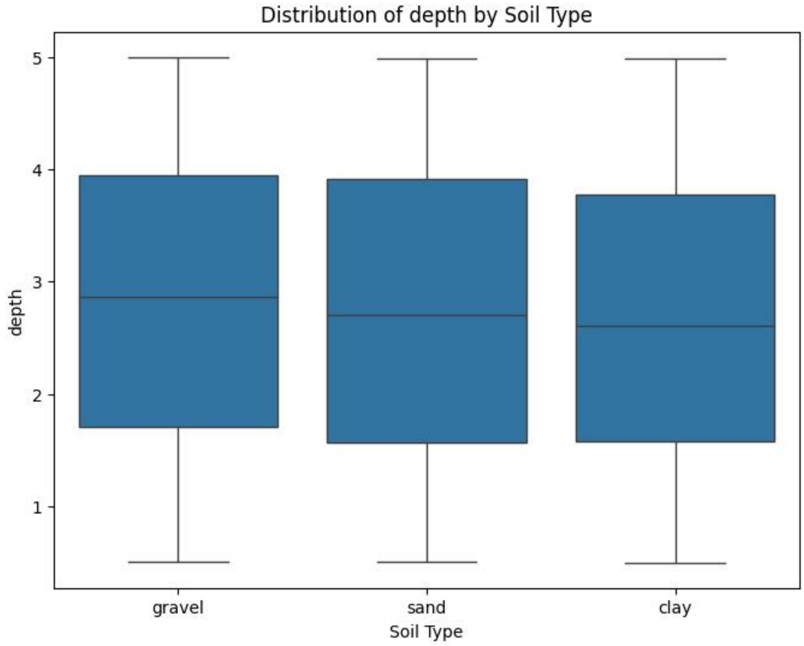


**Figure 5.** Distribution of Depth by Soil Type

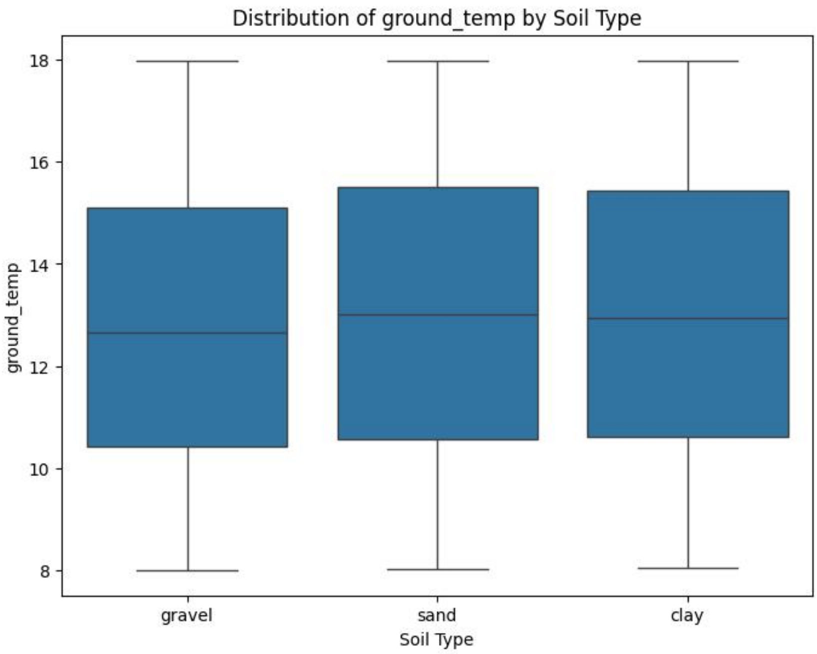


**Figure 6.** Distribution of Ground Temperature by Soil Type

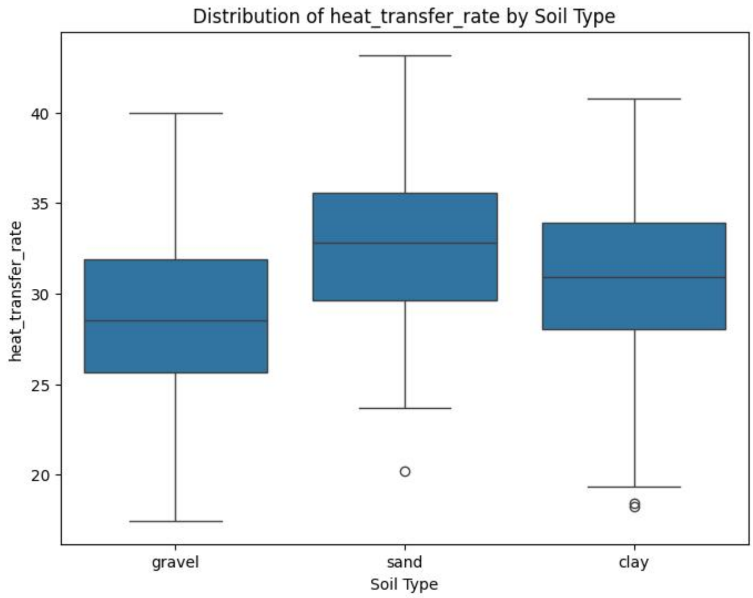


**Figure 7.** Distribution of Heat Transfer Rate by Soil Type

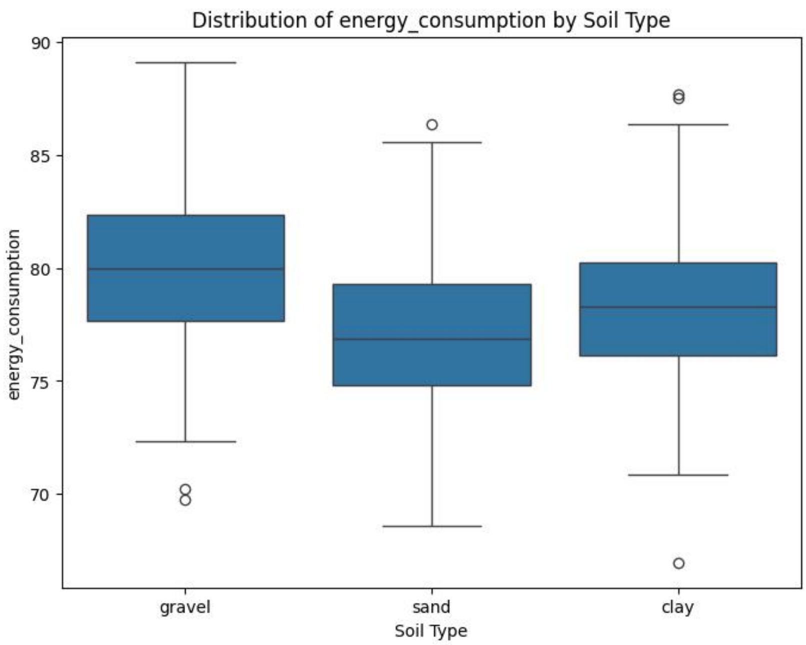


**Figure 8.** Distribution of Energy Consumption by Soil Type

Ground temperature (Figure 3) also showed similar distributions, confirming that observed differences in outcomes could be attributed primarily to insulation and soil type, not temperature bias. Figure 4 revealed that sand generally produced the highest heat transfer rates, followed by clay and then gravel, consistent with the higher conductivity coefficient assigned to sand. Energy consumption patterns (Figure 5) inversely reflected heat transfer rates, where sand-based systems consumed slightly less energy.

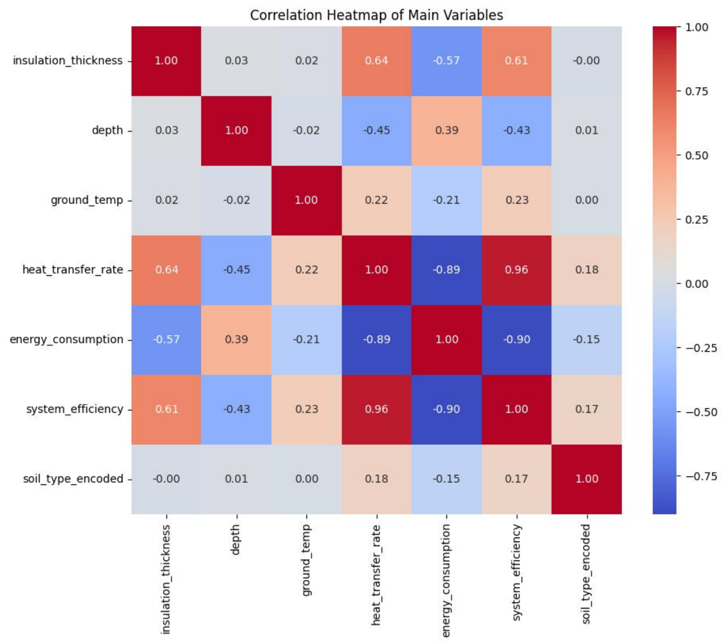


**Figure 9.** Heat Map

The correlation heatmap (Figure 6) highlighted several key insights. Insulation thickness was positively correlated with heat transfer rate (0.64) and system efficiency (0.61), while depth was negatively correlated with both (-0.45 and -0.43, respectively). Heat transfer rate was very strongly correlated with efficiency (0.96), and energy consumption was negatively associated with both heat transfer rate (-0.89) and efficiency (-0.90). These strong correlations justified the use of these variables in predictive and classification modelling.

### Predictive Models and Metrics

Three regression models—Random Forest Regressor, XGBoost Regressor, and Support Vector Regressor (SVR)—were trained to predict energy consumption. Table 3 summarises their performance metrics.

**Table 3.** Predictive Model Performance

| Model | MSE | RMSE | MAE | $R^2$ Score |
|---|---|---|---|---|
| Random Forest Regressor | 4.86 | 2.20 | 1.79 | 0.54 |
| XGBoost Regressor | 5.06 | 2.25 | 1.83 | 0.52 |
| Support Vector Regressor | 4.38 | 2.09 | 1.69 | 0.58 |

Among the three, the Support Vector Regressor slightly outperformed the others with the lowest Mean Squared Error (4.38), Root Mean Squared Error (2.09), and Mean Absolute Error (1.69), along with the highest $R^2$ value (0.58). This indicates it was the most accurate in predicting energy consumption, capturing nearly 58% of the variance in the target variable. Although Random Forest and XGBoost achieved comparable performance, SVR slightly outperformed both, indicating that its kernel-based approach more effectively captured the nonlinear relationships in the data.

### Classification Models and Metrics

To classify system performance as effective or not, three models—Logistic Regression, Random Forest Classifier, and XGBoost Classifier—were evaluated using Accuracy, Precision, Recall (Sensitivity), Specificity, F1 Score, AUC, and Average Log Loss. Table 4 presents the results.

**Table 4.** Classification Model Performancce

| Model | Accuracy | Precision | Recall | Specificity | F1 Score | AUC | Avg Log Loss |
|---|---|---|---|---|---|---|---|
| Logistic Regression | 0.95 | 0.969 | 0.979 | 0.692 | 0.974 | 0.924 | 0.118 |
| Random Forest Classifier | 0.96 | 0.976 | 0.983 | 0.538 | 0.979 | 0.931 | 0.275 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| XGBoost Classifier | 0.94 | 0.972 | 0.969 | 0.615 | 0.970 | 0.939 | 0.174 |

All models demonstrated strong classification ability. Logistic Regression had high accuracy (95%) and balanced precision (0.969) and recall (0.979), though its specificity (0.692) was moderate. Random Forest achieved the highest accuracy (96%) and recall (0.983), but had slightly lower specificity (0.538) and higher log loss (0.275), suggesting overfitting. XGBoost offered the highest AUC (0.939), suggesting superior model generalizability.

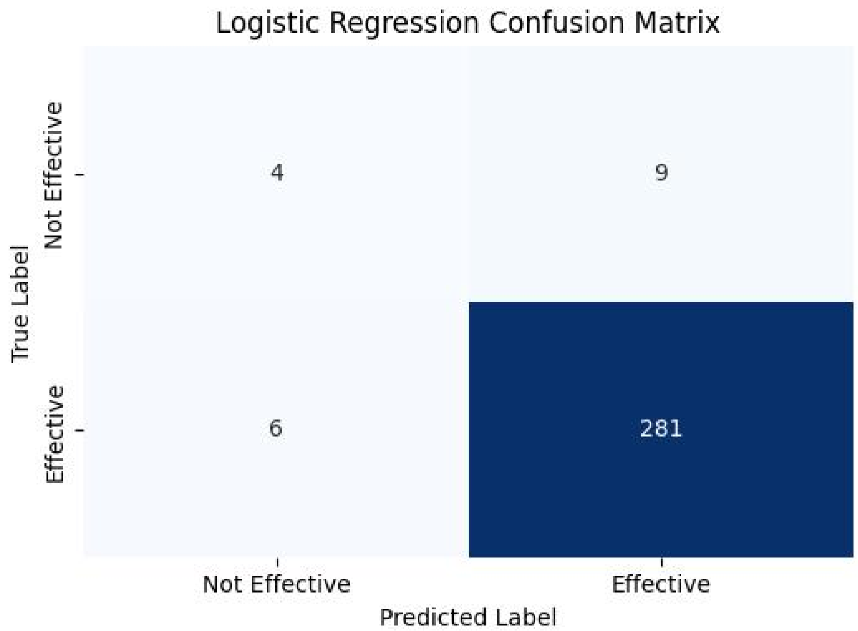


**Figure 10.** Confusion Matrix of Logistic Regression

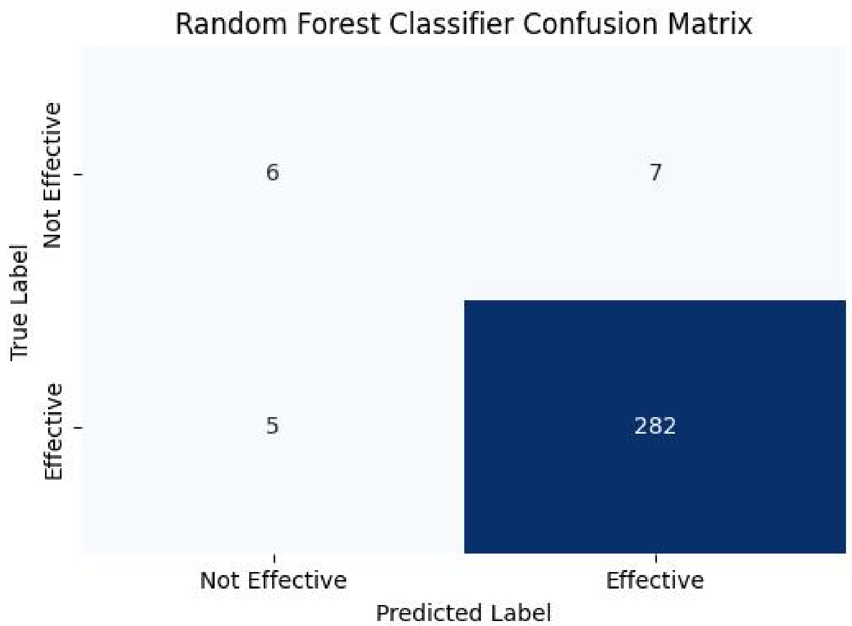


**Figure 11.** Confusion Matrix of Random Forest Classifier

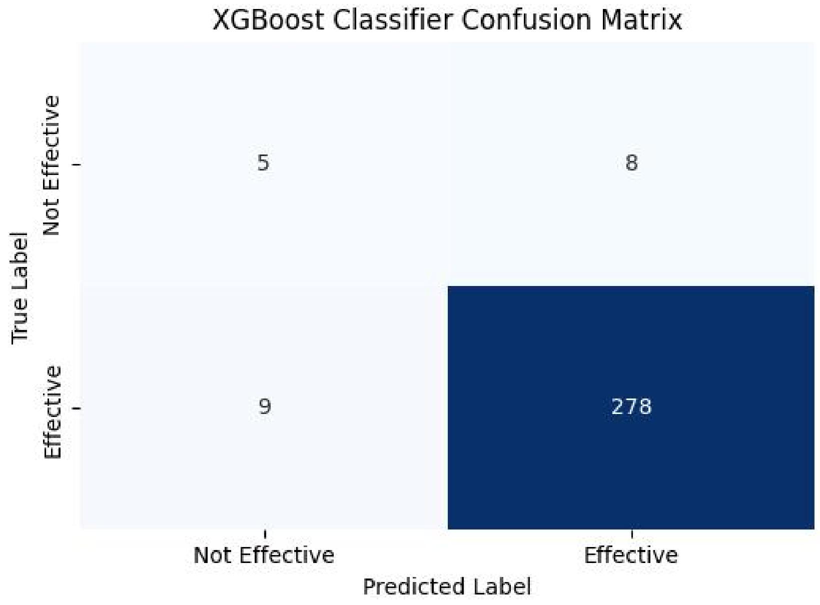


**Figure 12.** Confusion Matrix of XGBoost Classifier

Confusion matrices (Figures 7–9) further illustrate model performance. Logistic Regression misclassified 9 out of 13 ineffective systems, indicating a slight bias toward predicting effectiveness. Random Forest had a more balanced classification but still struggled with true negatives. XGBoost showed the most consistent performance in distinguishing between classes.

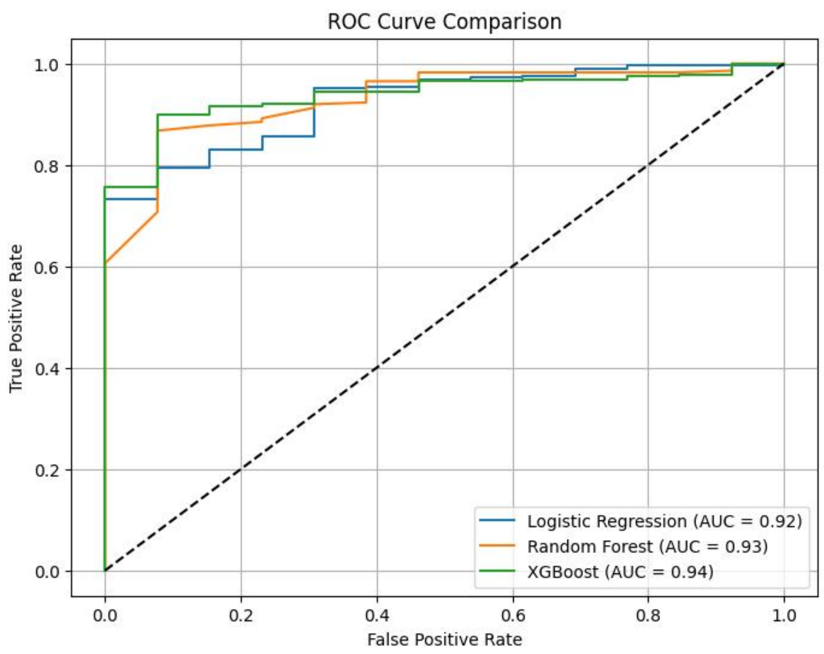


**Figure 13.** ROC-Curve

Figure 10 compares ROC curves for all three models. XGBoost displayed the best separation between classes, with an AUC of 0.94, followed closely by Random Forest (0.93) and Logistic Regression (0.92). This reinforces the findings that XGBoost strikes a strong balance between sensitivity and specificity, making it particularly effective in performance classification tasks for SGSHP systems.

It was determined that the insulation thickness and the type of soil have a significant impact on a heat pump's performance. The thicker insulation always gave better rates of heat transfer and efficiencies with sand-based systems. There was a negative relationship between depth and performance, and this fact proves that optimisation is more effective in shallow installations. Regional predictive models, such as SVR, were very successful in predicting energy consumption, whereas classification models, mainly XGBoost, succeeded in pinpointing the systems that worked well. These results confirm the application of simulation-based ML to SGSHP design and operation optimisation in shallow soils.

### Discussion

The discussion also agrees with the literature on three research objectives and compares the results with the past research on SGSHPs, insulation, strategy, and soil properties. The results indicated the influence of insulation thickness and the backfill soil on heat transfer. The results that thicker insulation contributes to better heat transfer and sand provides the highest thermal conduction are consistent with those of Sharaan et al. (2024) and Lin et al. (2023). Our results support Heo et al. (2022) because they found shallow systems in which insulation is sensitive. Zhang et al. (2020) found the effect of soil type on thermal distribution, and our simulation trends are in line. Lu et al. (2019) reported a decreased efficiency at depths greater than shallow strata, a situation that we replicated by using the observed depth and performance decrease. Moreover, the analysis shows forecasting energy consumption using ML regression. Out of Random Forest, XGBoost, and SVR, SVR had the lowest RMSE and MAE and the highest R2, as in Gasmi et al. (2024). The performance of ensemble models was moderate, which is in line with Gorai et al. (2024). Our normalised features and strong training-test divisions enable the efficacy of SVR, similar to Peng et al. (2020) and Ahmad (2025). The article shows that open-source applications such as Google Colab can be used for simulation-driven analysis, which can provide ML in sustainable energy systems (Lee et al., 2021). The analysis evaluated the classification of system effectiveness. XGBoost has the highest AUC (0.94) and then Random Forest (0.93), which means that it is more effective in discrimination. These findings confirm Zdravkovic et al. (2024). The specificity of the outcome (0.69) presented by the Logistic Regression is higher than that produced by the Random Forest (0.54), as Nanjundan et al. (2022) assert. Findings are also consistent with Zhao et al. (2021) and Bui et al. (2020) in terms of the significance of high AUC and low log loss. The sensitivity and specificity ratios of XGBoost confirm its utility in performance evaluation, which resorts to simulation data to live decisions (Jeong et al., 2022).

## CONCLUSION

Altogether, the work shows that simulation-driven data and ML models can be effective in assessing the impact of radiation-insulation films and backfill soils on the performance of shallow SGSHP. There is a positive correlation between insulation thickness and rates of heat transfer, particularly in sand soils, and the shallow installations are the most beneficial. The superior prediction of energy consumption is achieved by SVR, whereas the most effective classification of the system effectiveness is provided by XGBoost. These findings confirm the literature on the subject and point to the feasibility of simulation- and AI-based methods of SGSHP evaluation and optimisation. A combination of descriptive statistics, regression and classification models provides a comprehensive overview of the regime at variable thermal and soil settings and contributes to the ML application in sustainable energy engineering.

### Implications

Theoretical Implications

The study enhances the theoretical understanding of SGSHP performance by reaffirming the significance of shallow-depth dynamics, insulation design, and soil thermal properties. It provides empirical support for applying thermodynamic and ML-based modelling frameworks to analyse sub-surface energy systems. Furthermore, the results strengthen the argument that thermal performance can be abstracted into predictive and classification models to test engineering hypotheses, contributing to emerging theories of geothermal optimisation using AI.

Practical Implications

Practically, the research offers valuable insights to engineers, energy planners, and environmental designers. By identifying optimal configurations through simulated experiments, this study can inform decisions on selecting insulation thickness, choosing soil backfill, and system depth. The proven effectiveness of ML models like SVR and XGBoost in forecasting and classification also provides a practical toolset for future system design validation. The use of Google Colab further promotes accessibility and cost-effective research execution for SMEs and researchers.

### Recommendation

Based on the results, it is recommended that system designers prioritise the use of sand-based soils and install radiation insulation layers of sufficient thickness (10–15 mm) to optimise thermal performance. For installations within five meters, soil characteristics and insulation design should be considered in tandem, not in isolation. Moreover, predictive modelling using SVR or XGBoost should be adopted in early design simulations to evaluate different configurations before physical deployment. Researchers should also explore coupling simulation environments with real-time sensor data to improve model generalisation. Government bodies and sustainability agencies can leverage these models to develop policies for eco-friendly geothermal system installations, particularly in urban retrofitting projects.

### Limitations and Future Work

Despite its contributions, this study has several limitations. First, the data used were entirely simulation-based, which, while useful for controlled experimentation, may not fully capture the stochastic nature of real-world ground source heat pump systems. Additionally, only three soil types were included, and the insulation effects were simplified using uniform material assumptions. The performance threshold for classification (efficiency > 0.28) was arbitrarily selected and could differ in practical scenarios. Future research should integrate real-world datasets from monitored geothermal systems to validate the simulation logic. Expanding the model to include additional features like soil moisture content, insulation material conductivity, or seasonal thermal shifts could improve prediction accuracy. Further comparative analysis using deep learning models and hybrid ensemble strategies can also enhance classification reliability. Collaborations with field engineers and urban developers are encouraged to embed these ML frameworks into practical project assessments, ensuring greater transferability from simulation to implementation.

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