

Assessing The Impact Of Subsurface Uncertainty On CO₂ Plume Geothermal Performance

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Keywords: CO₂ plume geothermal, Geological uncertainty, Reservoir simulation

ABSTRACT

Meeting global energy demands while reducing greenhouse gas emissions requires both clean energy sources and carbon management strategies. Geothermal energy is a reliable and renewable resource that provides continuous power and is not affected by weather. At the same time, carbon capture, utilization, and storage (CCUS) technologies are essential for reducing CO₂ emissions from industrial activities. One innovative approach that connects these two goals is CO₂ Plume Geothermal (CPG) systems, which uses captured CO₂ as a working fluid to extract heat from the subsurface while also storing the CO₂ underground. However, the performance of CPG systems is highly affected by geological uncertainty, such as variations in rock properties and fluid flow behaviour. Understanding and quantifying these uncertainties is important for predicting energy output and designing effective geothermal systems. This study investigates the potential of CPG systems using the Egg model, a synthetic reservoir with 100 different permeability realizations. Reservoir simulations were performed using tNavigator to explore how changes in relative permeability, reservoir temperature, and injection temperature, along with uncertain geological parameters, influence key outcomes such as production well temperatures and total energy output. Furthermore, by applying dominant input parameters and Monte Carlo simulation, 2121 simulation samples were generated to obtain the distribution of key outputs. These results support better decision-making for geothermal development and emphasize the importance of quantifying geological uncertainty when designing CPG systems.

1 INTRODUCTION

A country's growth depends on a steady supply of energy and electricity. As the population increases and industries continue to develop, global electricity production is expected to rise sharply. Current annual electricity generation is about 30,000 TWh_e, and projections estimate that demand will reach between 31000-35000 TWh_e by 2030, 39000-43000 TWh_e by 2040, and 47000-50000 TWh_e by 2050 (Lopez et al., 2024). To meet this rising electricity demand while supporting net-zero targets and minimizing environmental impacts, a transition from fossil fuels to renewable energy sources is essential. Geothermal energy production, which harnesses heat from within the Earth, is considered a clean and sustainable renewable resource. Geothermal energy is always available regardless of time or weather conditions, making it a highly stable and reliable energy option (Nath et al., 2024).

The global utilisation of geothermal energy is expanding rapidly for both electricity generation and heating purposes. From 2010 to 2023, the worldwide installed geothermal power capacity grew from 10897 MW_e to 16318 MW_e (Gutiérrez-Negrín, 2024). The International Energy Agency (IEA) projects that geothermal energy could provide nearly 3.5% of the world's electricity supply in the future (Rohit et al., 2023), although its share in 2023 was below 0.5% (Gutiérrez-Negrín, 2024). This significant projected growth highlights the need for innovative technologies.

One such technology is CO₂ Plume Geothermal (CPG). In CPG systems, large volumes of CO₂ are injected into naturally permeable reservoirs, forming a subsurface plume that absorbs heat from the surrounding rock and is then produced to generate energy, with no need for reservoir stimulation (Randolph & Saar, 2011). That is, rather than treating CO₂ as a waste product in Carbon Capture and Storage (CCS) projects, it can be utilized as a working fluid for geothermal energy production (Esteves et al., 2019). CPG differs from CO₂-based Enhanced Geothermal Systems (EGS), which use CO₂ in low-permeability, engineered reservoirs that require hydraulic fracturing or other stimulation to create flow paths (Brown, 2000; Esteves et al., 2019). Because CPG use reservoirs that are already naturally permeable and do not involve fracturing, it generally carries a lower risk of induced seismicity (Randolph & Saar, 2011).

Previous research shows that CPG systems offer several advantages over conventional water-based geothermal systems. CO₂ has better mobility and higher thermal expansibility (Atrens et al., 2010). These characteristics not only make up for CO₂'s lower specific heat capacity compared to water but can also lead to the creation of a strong thermosiphon, which is a gravity-driven circulation process that moves fluid without needing a pump (Garapati et al., 2015; Schifflechner et al., 2024). Another benefit is that CO₂'s non-polar nature decreases the chances of scale buildup in wellbores and surface facilities (Zhong et al., 2023). In addition, CPG simultaneously achieves permanent geological storage of a portion of the injected CO₂, allowing operators to earn CO₂ credits that can be traded or sold in certain countries (Pongtuluran et al., 2024). Figure 1 shows main steps in a CPG system.

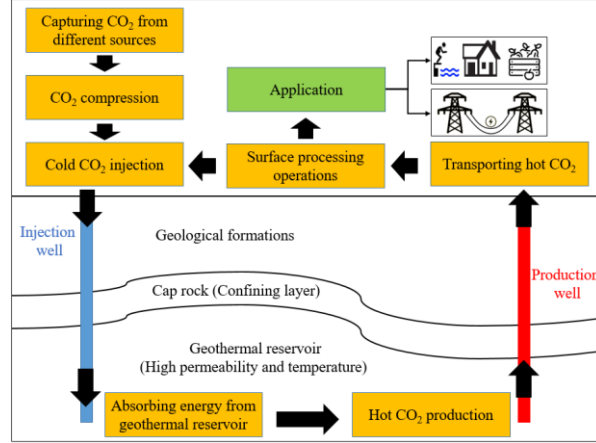


Figure 1. Simplified schematic of a CPG system.

Uncertainty quantification plays a crucial role for reliable decision-making from any reservoir modelling exercise (Fathy et al., 2024). This is no different for CPG systems. Considering all possible realizations of a sub-surface system is essential for a full quantification of uncertainty, but the large number of geological uncertainties typically makes it computationally impossible to simulate every possible scenario.

In this study, we investigated the impact of subsurface uncertainty on the predicted performance of CPG systems. We first performed a sensitivity analysis on selected parameters to evaluate their influence on key outputs such as total lifetime energy production. Based on this analysis, the most influential parameters were identified and varied in simulations to quantify the uncertainty in the final outputs. For this purpose, we used a standard benchmark reservoir model known as the Egg Model (Jansen et al., 2014). In the following sections, we describe the Egg Model and our methodology in detail. We then present and discuss the results of our simulations and finally provide the main conclusions.

2 METHODOLOGY

Our workflow is illustrated in Figure 2. The process began with the model setup, where two numerical models were constructed to represent both CPG and water-based geothermal energy production systems. The reservoir geometry, boundary conditions, and well configurations were the same for both fluid types.

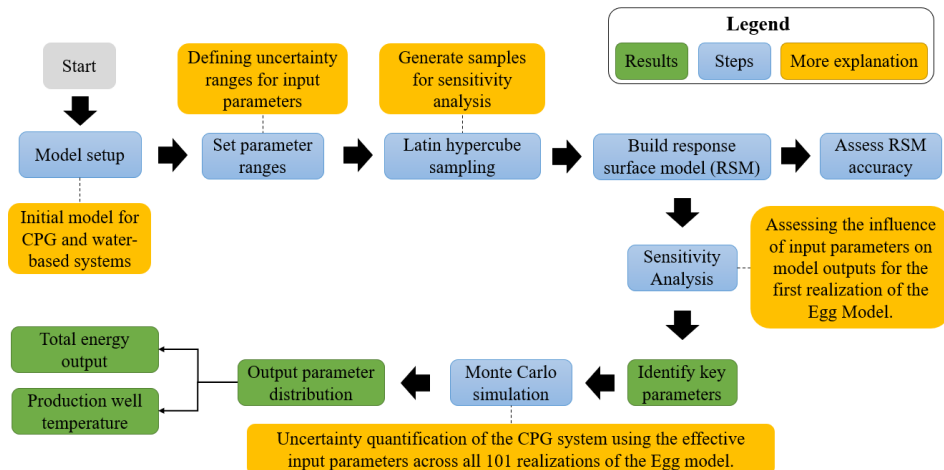


Figure 2. The flowchart of the proposed methodology.

Following model initialization, the uncertainty ranges for input parameters were defined to account for natural variability and data limitations in subsurface characterization. As a result, six input parameters were selected to assess their influence on total thermal energy production and production bottom hole temperature. The selected parameters and their corresponding variation ranges are summarized in Table 1. These ranges are based on values commonly reported for sandstone and carbonate reservoirs. For example, the CO₂-brine-rock system is generally water-wet or slightly water-wet (Baban et al., 2021). Furthermore, the base porosity value used here is identical to that reported in the original Egg Model study (Jansen et al., 2014). The values listed in the “Base” column of Table 1 were applied for the base-case simulations. All simulations in this study were performed using the tNavigator reservoir simulation software (Rock Flow Dynamics).

Table 1. Uncertain parameters and their ranges.

Parameter	Base	Distribution	Options
Relative permeability	1	Discrete (1,3)	Strongly water-wet, slightly water-wet, neutral
Initial reservoir temperature (°C)	125	Uniform (min= 100, max= 150)	
CO ₂ injection temperature (°C)	35	Uniform (min= 30, max= 40)	
Rock thermal conductivity (W/mK)	2.89	Uniform (min= 1.736, max=4.05)	
Reservoir porosity	0.2	Uniform (min= 0.175, 0.225)	
Rock compressibility (1/bar)	2.00E-05	Uniform (min= 1.00E-5, max= 8.00E-5)	

To efficiently explore the uncertainty space, Latin Hypercube Sampling (LHS) was employed to generate a representative set of input samples based on the data in Table 1. LHS is a statistical method used to efficiently explore uncertainty in model parameters. Instead of randomly selecting values, LHS divides the range of each input parameter into equal intervals and ensures that each interval is sampled exactly once (Helton & Davis, 2003). The samples generated by LHS were used as inputs into our simulations to develop a Response Surface Model (RSM), which provides a mathematical approximation of the relationship between the input parameters and the simulation outputs. Once generated, an RSM subsequently acts as a surrogate to the main numerical model, allowing fast predictions of system behaviour without repeatedly running computationally expensive simulations (Khuri & Mukhopadhyay, 2010). In this study, we used second-degree (quadratic) RSMs to identify the influence of each parameter on the selected output responses. The general form of a quadratic RSM can be expressed as (Khuri & Mukhopadhyay, 2010):

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j}^k \beta_{ij} x_i x_j + \epsilon \quad (1)$$

where k is the number of input parameters, y is the predicted response, x_i represents the input parameters, β_0 is the intercept, β_i , β_{ii} , and β_{ij} are the coefficients of the linear, quadratic, and interaction terms, respectively, and ϵ is the error term.

As mentioned in Table 1, six input parameters were initially considered. Among them, five were continuous variables, and one was a categorical parameter (relative permeability). Since three different options were used for relative permeability (see Table 1), it was encoded into two binary variables to be compatible with the RSM framework. Each binary variable could take a value of 0 or 1; if one of them was 1, the other had to be 0. When both were 0, it indicated that the third option was selected. Furthermore, during the pre-processing stage, all continuous variables were normalized to a range between 0 and 1. Consequently, after pre-processing, the number of input parameters increased from six to seven. The number of terms in a second-degree RSM is determined using the following equation (Khuri & Mukhopadhyay, 2010):

$$p = 1 + 2k + \frac{1}{2}k(k - 1) \quad (2)$$

In our case, $k=7$, resulting in 36 terms in the model. Therefore, the minimum number of design points required to construct the RSM is also 36. However, to enhance model accuracy, a total of 300 samples were generated using LHS method. Out of these, 250 samples were used for training the model and estimating its parameters, and 50 samples were kept separate and were not used during model development; instead, they were used to evaluate how well the trained model performs on unseen data. This RSM was employed for the sensitivity analysis. Additionally, k -fold cross-validation was applied to further evaluate and validate the accuracy of the developed RSM. In this method, the dataset is divided into k subsets. The model is trained on $k-1$ parts and tested on the remaining part, and this process is repeated k times. This approach offers a more robust evaluation than a single train-test split, mitigating overfitting, reducing bias, and enhancing the model's ability to generalize predictions to real-world scenarios (Wong & Yeh, 2020). In this study, we used 5 folds, and R^2 score is used to measure the model's goodness of fit. Once validated, a sensitivity analysis is performed on the RSM to quantify the relative influence of each uncertain input on key performance metrics, such as energy output. This step identifies which parameters most strongly control system behaviour. The parameters exhibiting the highest sensitivity are then classified as key parameters, representing the dominant factors affecting CPG system performance.

So far, all simulations for the sensitivity analysis and the RSM were performed based on the first realization of the Egg Model to identify the most important input parameters for the outputs of interest, although the model has 101 realizations. Therefore, in the next step, a Monte Carlo simulation was conducted using random sampling of key parameters from their associated probability distributions to generate a specific number of system samples across all 101 realizations. This statistical approach provided a probabilistic representation of the model outcomes and captured the overall uncertainty in the model (Helton & Davis, 2003). Finally, the output parameter distributions were analysed. Parameters such as total energy output and production well temperature were examined to assess the efficiency of the CPG system.

3 CASE STUDY DESCRIPTION

In this study, the Egg Model was used as a benchmark case to investigate the performance of CPG and water-based geothermal reservoirs under geological uncertainty. The Egg Model is a synthetic, three-dimensional reservoir ensemble developed at Delft University of Technology (Jansen et al., 2014). It was initially designed and widely applied in oil and gas studies focusing on reservoir simulation, optimization, and uncertainty analysis, but has recently been adopted for geothermal reservoir modelling as well (Tian et al., 2024). The model comprises 101 realizations representing a fluvial-type, channelized clastic sedimentary reservoir discretised into a $60 \times 60 \times 7$ three-dimensional grid (25,200 cells), of which 18,553 are active. Each realization contains a unique permeability pattern with high-permeability channels distributed within a low-permeability background (Jansen et al., 2014). In this study, a pair of production and injection wells was assumed, each fully perforated throughout the reservoir thickness. The locations of the wells were kept fixed across all simulations to maintain consistent conditions for sensitivity analysis and uncertainty quantification. The reservoir and well properties used in the simulations are summarized in Table 2.

Table 2. Reservoir and well properties used for numerical simulation.

Parameter	Value (unit)	Parameter	Value (unit)
Number of grid cells	X=60, Y=60, Z=7	Grid size in x direction	30 m
Reservoir initial pressure at datum depth (4000 m)	40000000 Pa (400 bar)	Grid size in y direction	30 m
production condition	Constant Bottom hole pressure (35000000 Pa)	Grid size in z direction	10 m
Injection condition	Constant Bottom hole pressure (41000000 Pa)	Rock volumetric heat capacity	2000000 J/m ³ /K
Reservoir depth	4000 m	Simulation runtime	9000 days
Location of production well (based on grid)	X = 16, Y=43	Location of injection well (based on grid)	X= 40, Y= 20

4 RESULTS AND DISCUSSION

This section presents the results of the numerical simulations, sensitivity analysis, and uncertainty quantification conducted for the CPG systems using the Egg Model framework.

4.1 Base-Case Simulation

Figure 3 illustrates the changes in CO₂ saturation over time using Base Case parameter values for the first permeability realization of the Egg Model assuming a CPG (as opposed to water-based system). Red and yellow arrows indicate the locations of the production and injection wells, respectively.

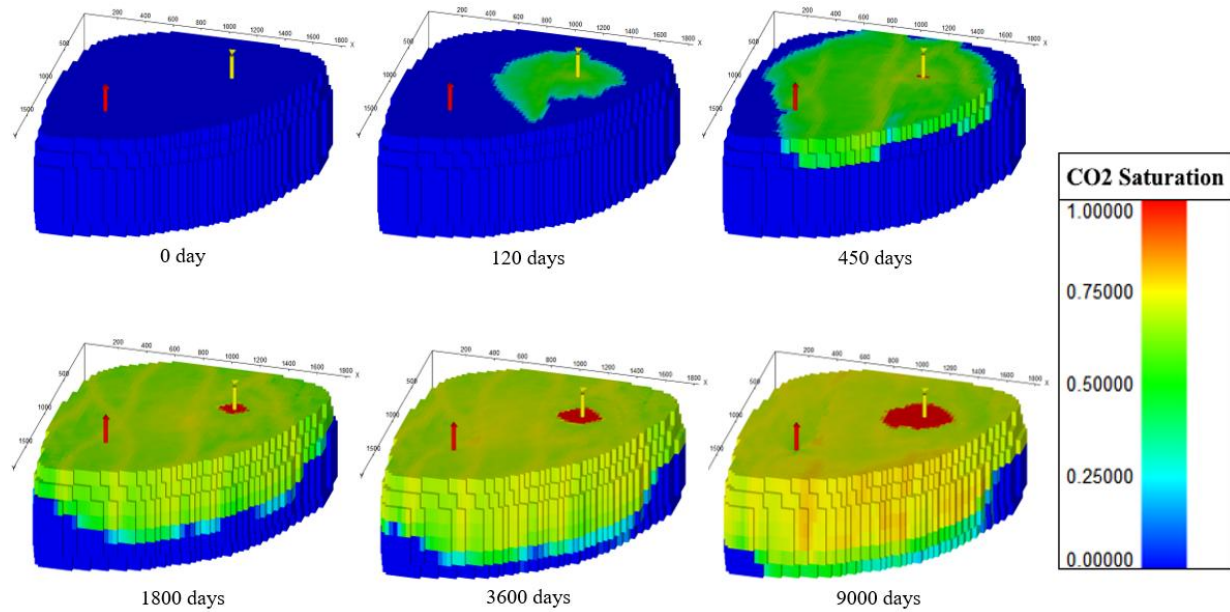


Figure 3. CO₂ saturation distribution over time for the first permeability realization of the Egg Model for the base case CPG system.

Figures 4 illustrates the production well bottom hole temperature for the same permeability realization for both CPG and water-based geothermal systems. As seen in Figure 4, the production well bottom hole temperature was 125°C for approximately the first 1500 days for both the CPG and water-based systems. The CPG system, however, experienced a faster and steeper temperature decline than the water-based system, cooling to around 90°C after 4000 days (~11 years) and 60°C after 9000 days (~25 years). By comparison, the water-based system was >110°C after 4000 days and about 70°C after 9000 days.

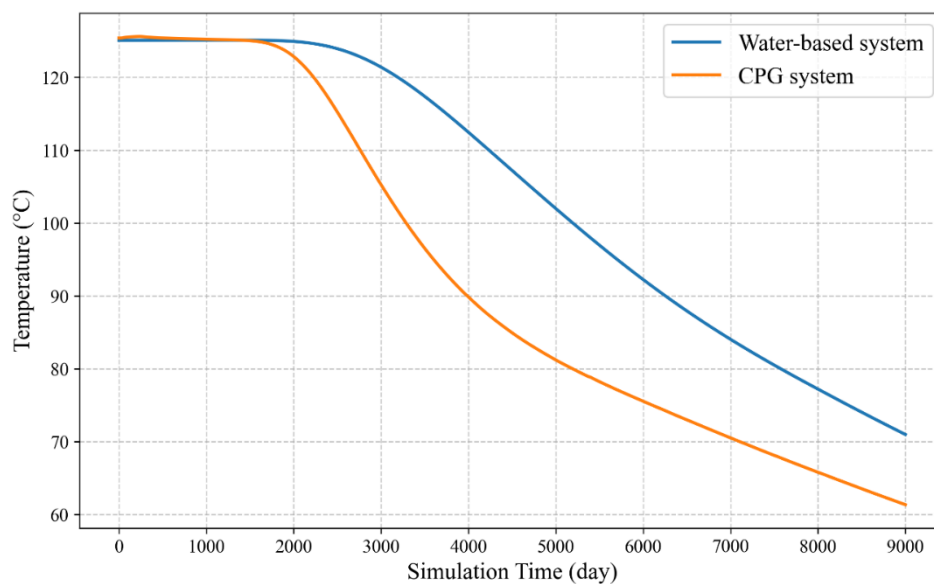


Figure 4. Bottom hole temperature of the production wells for both the CPG and water-based systems.

Figure 5 shows the predicted thermal energy production rate for the same permeability realization for both CPG and water-based geothermal systems. The energy production rate was calculated from the enthalpy difference between the fluid produced at the production well and a reference condition defined as a temperature of 60°C and a pressure of 1 bar. The result exhibits a similar declining trend to the bottom hole temperature profile. At the beginning of the simulation, the CPG system produces a higher thermal energy rate than the water-based system due to the higher mobility of CO₂. However, as production continues, the CPG system experiences an earlier and more rapid decline in thermal energy output, due to the faster temperature drop observed in Figure 4. In contrast, the water-based system demonstrates a more stable energy production rate over time.

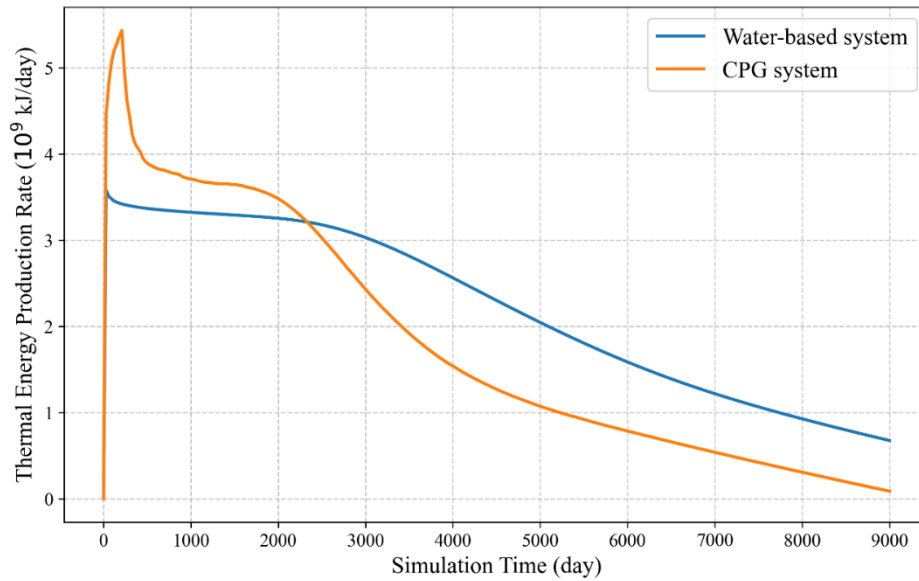


Figure 5. Comparison of thermal energy production rate for the CPG and water-based systems over time.

4.2 Sensitivity Analysis

In this study, two separate RSMs were constructed: one for predicting the total energy production and another to predict the production well bottom hole temperature at the end of the simulation period (9000 days). Table 3 presents the accuracy metrics of the RSM models for these two output parameters. The R^2 values for both RSMs are very close to 1, indicating high model accuracy. Therefore, the developed RSMs can be considered reliable for performing the sensitivity analysis.

Table 3. Accuracy evaluation of the developed RSMs for predicting total energy production and bottom hole temperature.

Predicted output	Accuracy assessment method	R^2
Total energy production	Training and test sets	0.999919228
Bottom hole temperature	Training and test sets	0.999943338
Total energy production	Five-fold cross validation	0.999753672
Bottom hole temperature	Five-fold cross validation	0.999826015

Partial dependence plots (PDPs) were employed to examine how variations in individual input parameters influence the model outputs while averaging out the effects of all other variables. This approach provides an effective means of visualizing parameter sensitivity and identifying nonlinear relationships (Greenwell, 2017). Figures 6 and 7 present the PDPs for total energy production and bottom hole temperature, respectively. The relative permeability plots differ from the others because this parameter is categorical. In these plots, a relative permeability value of 1 represents a strongly water-wet condition, 2 indicates a slightly water-wet condition, and 3 corresponds to neutral wettability.

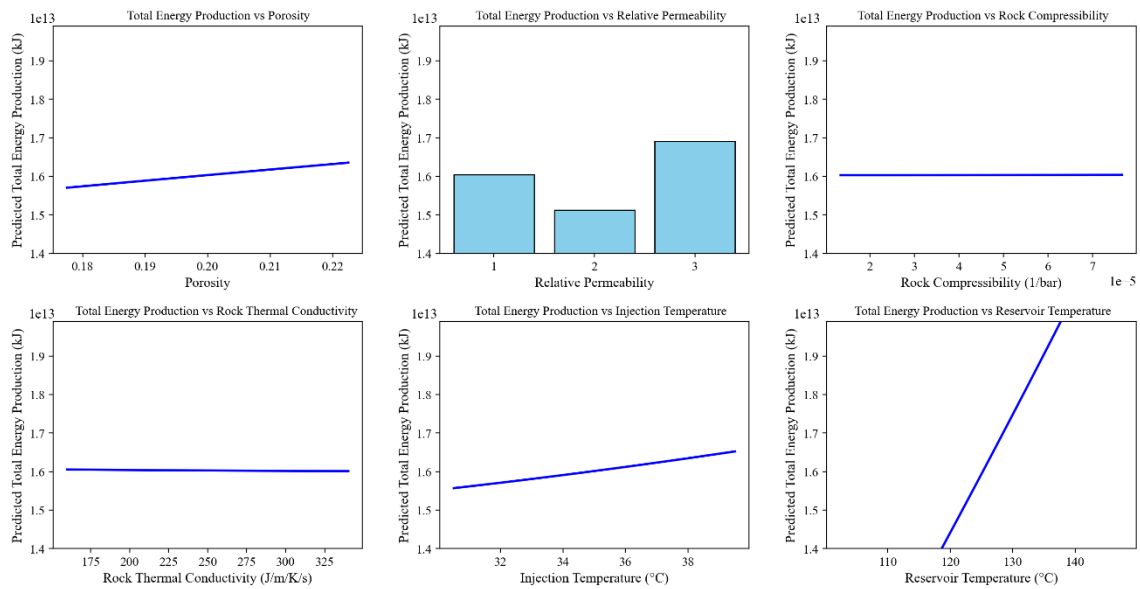


Figure 6. PDPs illustrating the influence of input parameters on total energy production over the full simulation time.

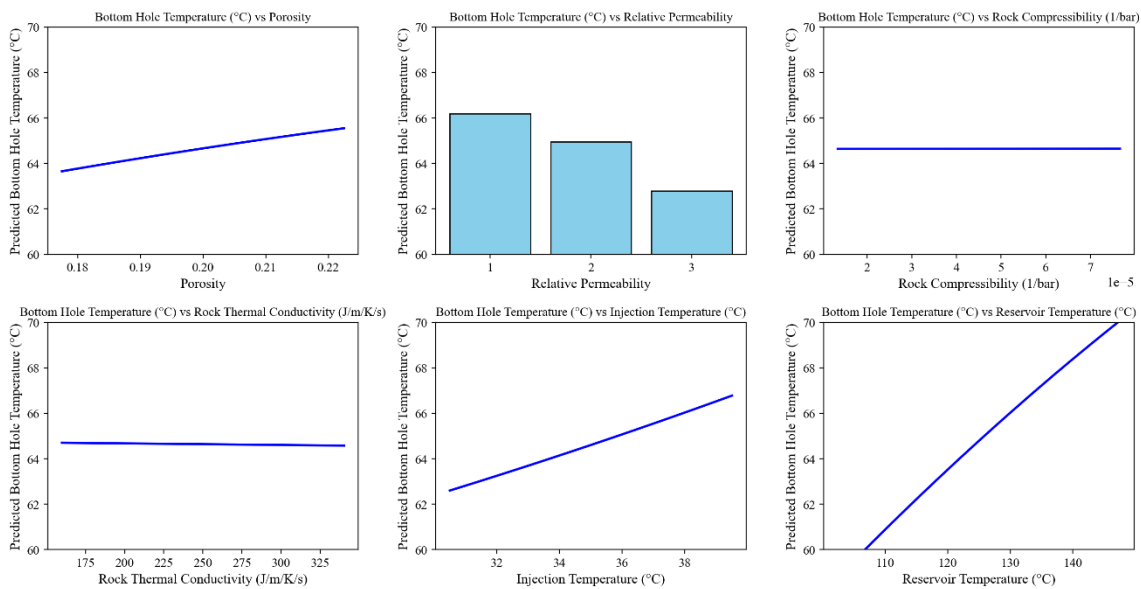


Figure 7. PDPs illustrating the influence of input parameters on production bottom hole temperature at the end of the simulation time.

Based on Figures 6 and 7, reservoir temperature is identified as the most influential parameter affecting the model outputs, followed by relative permeability, injection temperature, and porosity, which show moderate effects. In contrast, rock compressibility and rock thermal conductivity exhibit negligible influence on the results, so they were dropped from the analysis in the next step.

4.3 Uncertainty Quantification

Among the input parameters listed in Table 1, reservoir temperature, injection temperature, porosity, and relative permeability had the most significant influence on the model outputs of modelling the first realization of the Egg Model. Of those, injection temperature is not a geological uncertainty, since it is defined by operational settings. Therefore, a fixed injection temperature of 35°C was used in this part of the study. As explained in Section 3, the Egg Model includes 101 permeability realizations. To investigate the effect of geological uncertainty on the model outputs, we used Monte Carlo simulation to generate 21 samples of each of the 101 Egg Model realizations, applying varying values of reservoir temperature, porosity, and relative permeability within each realization for a total of 2121 simulations for the uncertainty quantification process. For porosity and reservoir temperature, uniform probability distributions were assumed during Monte Carlo sampling based on the ranges provided in Table 1. For relative permeability, the three different cases described in Table 1 were used.

Figure 8 presents the results for total energy production. In both figures, each grey line represents one of the 2121 simulations. In Figure 8, the left panel shows how total energy production is modelled to change over time, while the right panel displays the probability distribution of total energy production over the 2121 simulations. The distribution indicates a mean value of approximately 1.26×10^{13} kJ, a median of 1.27×10^{13} kJ, and a standard deviation of about 5.71×10^{12} kJ. Some of the model scenarios have negative total energy production. In those scenarios, the bottom hole temperature of the production well dropped below the reference temperature of 60°C early in the simulation.

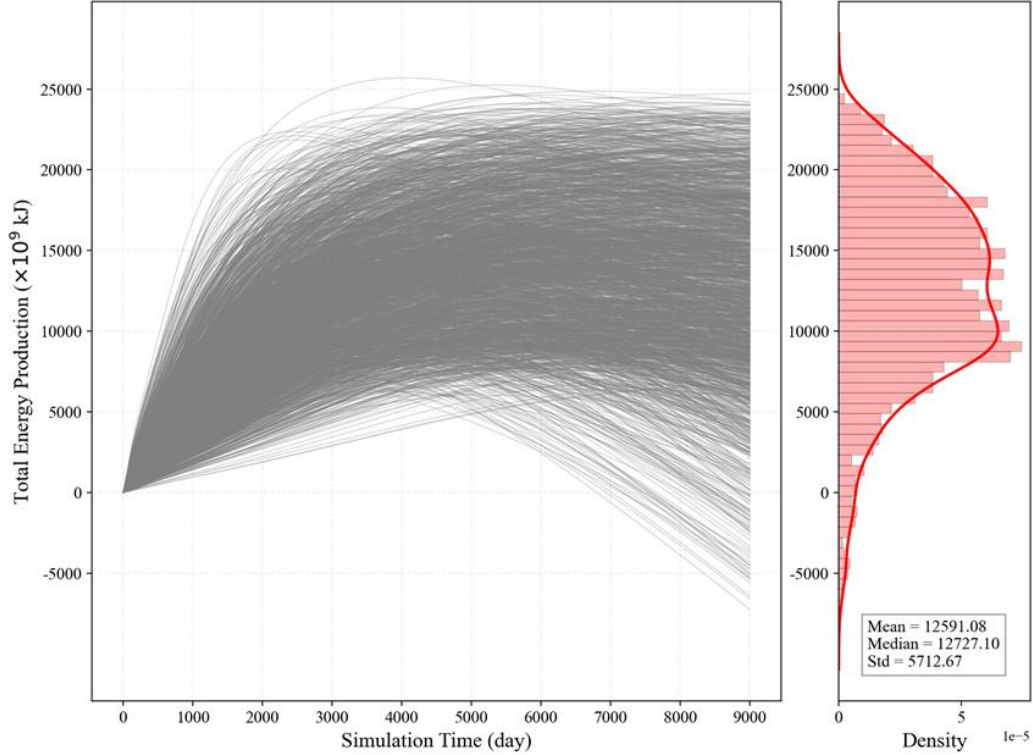


Figure 8. Monte Carlo simulation results for total energy production. The left panel shows the cumulative energy production over time, while the right panel illustrates the probability distribution of total energy production at the end of the simulation.

Figure 9 presents the results for and production well bottom-hole temperature. Initial reservoir temperature was one of the key input parameters considered for the uncertainty quantification, and a uniform probability distribution was applied over a range of 100°C to 150°C. This variation is clearly reflected in the spread of initial temperatures at zero simulation time and has a clear impact on the distribution of simulation results after 9000 days. The final distribution has a mean value of approximately 50 °C, a median of 49°C and a standard deviation of about 9°C.

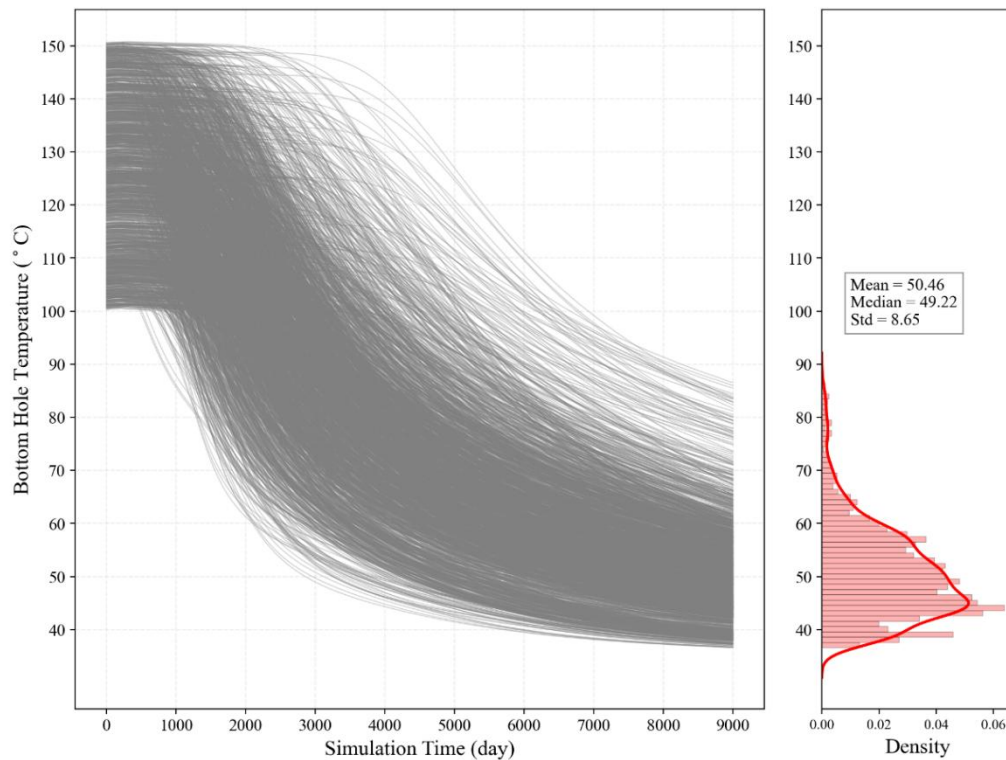


Figure 9. Monte Carlo simulation results for production well bottom hole temperature. The left panel presents the temperature variation over time for each of the 2,121 simulations, while the right panel shows the probability distribution of the production well bottom hole temperature at the end of the simulation.

5 CONCLUSIONS

This study assessed the influence of geological uncertainties on the performance of CPG systems using the Egg Model as a benchmark. Through a combination of sensitivity analysis, response surface modelling, and Monte Carlo simulations, key factors affecting total energy production and production well bottom hole temperature were identified. The analysis revealed that reservoir temperature is the most influential parameter, followed by relative permeability, injection temperature, and porosity. In contrast, rock thermal conductivity and rock compressibility showed negligible effects on system performance.

The base-case comparison between CPG and water-based geothermal systems indicated that while CO₂ delivers a higher initial thermal energy production rate due to its greater mobility, its performance declines faster over time relative to a water-based system because of rapid cooling at the production well.

Uncertainty quantification results based on 2121 simulations demonstrated a wide range of possible outcomes, emphasizing that small variations in key parameters can lead to significant differences in outputs like total energy production. These findings underline the importance of minimizing the uncertainty of key geological parameters as much as possible during the early design and feasibility assessment stages of CPG (and water based) geothermal energy production projects.

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